Gas path analysis for enhanced aero-engine condition monitoring and maintenance

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GAS PATH ANALYSIS
FOR ENHANCED AERO-ENGINE CONDITION MONITORING AND MAINTENANCE

Proefschrift

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To my parents and my dearest Jivika, Kira and Nikita.

"Life is what happens to you while you're busy making other plans."

John Lennon

Summary

Maintenance of aero-engines is essential for safe, reliable and cost-effective aircraft operations. Operational aero-engines deteriorate over time. This affects their mechanical and aero-thermodynamic performance and reduces engine safety, reliability and efficiency. However, maintenance is a major component of the cost per fired hour of a gas turbine. Because the engines are a relatively expensive component of an aircraft, aero-engine maintenance is an important subject for cost reduction.

Cost-effective maintenance of gas turbine aero-engines is achieved by combining two strategies: maintenance at fixed intervals and condition-based maintenance. Whereas maintenance at fixed intervals is specified by the engine manufacturer, condition-based maintenance is scheduled by the engine operator, which enables them to potentially optimize this process. Regular inspections, engine condition monitoring and performance diagnostics methods are used to establish the degree of deterioration for scheduling condition-based maintenance.

An important element in the maintenance process is engine overhaul. During this process an aero-engine is removed from the aircraft, disassembled, cleaned, inspected, repaired as necessary, and finally tested. Detailed knowledge of engine condition prior to overhaul provides engine operators and engine repair shops with the necessary information to plan overhaul work scopes and to help ensure a cost-effective process.

Condition monitoring methods can be used during engine tests and during in-flight operation. Traditional methods are capable of estimating the condition of the overall engine, but lack the ability of component-level condition estimation. A much better understanding of the actual condition per component can be obtained from detailed analysis of the complete engine gas path.

The goal of this research was to solve challenges encountered with the application of gas path analysis in the aero-engine maintenance process. Gas path analysis (GPA) is a performance diagnostic method that can identify engine modules responsible for engine performance problems without the need for engine removal or disassembly. It relates variations of measured engine performance parameters resulting from engine deterioration to the condition of its gas path components. The earliest GPA methods, which used linearized relations between condition parameters and performance parameters, were not sufficiently accurate for maintenance application. Advancements in performance modeling methods, numerical methods and computer platform technology have resulted in more accurate GPA methods that can be divided into two categories: empirical GPA methods and model-based GPA methods. Empirical GPA methods use measurements obtained from the field or experiments to correlate component condition to engine performance data, and use the inverse of those correlations to assess engine condition from measured performance. Model-based GPA methods, on the other hand, use thermodynamic principles to link measured engine performance parameters to gas path component condition. Even though empirical and model-based GPA methods are different in many aspects, all GPA methods require sufficient measured performance data and an accurate relation between gas path component condition and performance parameters to provide accurate results. In practice, limited engine operational data, inaccurate GPA tools and the absence of an information system means that often GPA is not used effectively or not used at all in the maintenance process.

This work is focused on three subjects. First, improving the accuracy and reliability of a non-linear, model-based GPA tool. Second, more effectively using available engine performance data for GPA. Third, developing an information system concept for GPA applications. Results were obtained by using both simulated gas turbine performance data as well as field data measured during engine performance tests and during in-flight operation. The Gas turbine Simulation Program (GSP) was used for performance simulation. GSP is a component-based performance simulation tool with a library of component sub-models that represent aero-thermodynamic gas path components, mechanical components and engine control components. GSP has a generic adaptive modeling (AM) capability that can be used for model-based GPA.

The first important element of this work has been improving the accuracy and reliability of model-based GPA results. Even though changes in component condition from a performance perspective cannot be directly measured, they can be modeled. More importantly, deterioration effects can be observed by changes in performance parameters. GPA tools calculate deviations of an engine's gas path component condition relative to a reference engine. Model-based GPA tools use gas turbine performance models to calculate these deviations. Two sources that affect the accuracy of model-based GPA are the accuracy of the performance model and the reference engine used.

Gas turbine performance models use the thermodynamic laws of conservation of mass, energy and momentum to simulate the interaction among gas path components. To simulate the behavior of individual gas path components at various operating conditions, so-called component maps are used. Because component maps describe the behavior of actual gas path components, the accuracy of gas turbine performance models is strongly dependent on the accuracy of these component maps. However, gas turbine manufacturers consider such detailed data proprietary and as a result the required component maps for creating accurate performance models are not available outside the manufacturers' domain. The common alternative is to use component maps that are available in the public domain and scaling them such that they sufficiently represent the desired component. However, scaled component maps, which are usually scaled relative to a single operating point, are not sufficiently accurate for GPA. To overcome this challenge, a more detailed scaling method was investigated that used large volumes of on-wing measured performance data of recently overhauled engines. By using large volumes of engine performance data available for a wide operating range, the component maps could be tuned with more detail. The tuned maps captured the behavior of the real gas path component more accurately and thereby improved the accuracy of GPA results.

Additional improvements to the accuracy and reliability of GPA were obtained by using multiple reference engines to calculate the condition of an engine. Because operational engines with a good overall condition, which can serve as a reference engine, still show significant component condition deviations relative to each other, selecting the right engine is important for obtaining reliable GPA results. Because every engine has its own deterioration and maintenance history, selecting a reference engine by considering only its overall condition may not be sufficient. Using multiple reference engines for estimating the condition of a single engine takes this engine-to-engine variation into account and improves the reliability of the GPA results. Because each reference engine provides slightly different component condition estimations, the variation of multiple reference engines provides a way to visualize the uncertainty of the estimated component condition.

The second important element has been the development of methods to more effectively use GPA in the aero-engine maintenance process. Traditionally, engine performance after overhaul is tested during mandatory performance acceptance tests. Because those tests are expensive and time-consuming few engines are tested before being overhauled. As a result, maintenance work scopes are often planned without knowing the detailed condition of gas path components. Because efficient gas turbine operation is the result of a fine-tuned balance among the performance of its gas path components, knowing their condition is essential for effective maintenance. On-wing measured performance data would provide an excellent opportunity to obtain that information. By analyzing those data with GPA, detailed in-flight component condition data can be obtained, which provides an excellent alternative to performance tests prior to engine overhaul at minimal additional cost and time.

The third important element of this work was the development of an information system concept for GPA application. It includes a relational database, which contains data available from the aero-engine maintenance and operational processes. This database was coupled to the GSP GPA analysis tool and has been used for demonstrating the added value of systematically using GPA in the aero-engine maintenance process.

The results of this research work led to the development of new methods that were implemented in GSP. The added value has been demonstrated on a large fleet of commercial turbofan engines. In the competitive field of gas turbine maintenance, repair and overhaul accurate engine condition monitoring and performance diagnostic tools may provide a technological advantage over competitors who can provide similar maintenance and overhaul services at lower rates. These developments are a step towards systematically using GPA in the aero-engine maintenance process and thereby help to further improve safe, reliable and cost-effective airline operations.

Samenvatting

Onderhoud van vliegtuigmotoren is essentieel voor veilige, betrouwbare en renabele luchtvaart. Operationele motoren slijten. Dit beïnvloed de mechanische en aero-thermodynamische prestaties van de motor en heeft een nadelig effect op de veiligheid, de betrouwbaarheid en het rendement. Onderhoud dat nodig is om de effecten van slijtage tegen te gaan is een belangrijk element van de totale kosten per vlieguur. Daarom wordt het onderhoud van vliegtuigmotoren gezien als een belangrijke kandidaat voor mogelijke kostenreductie.

Een kosteneffectief onderhoudsproces van vliegtuigmotoren kan worden gerealiseerd door onderhoud op vaste intervallen te combineren met onderhoud op basis van conditie. Hierbij word het onderhoud op vaste intervallen door de motorfabrikant bepaald, terwijl de motorgebruiker zelf het onderhoud op basis van motorconditie kan bepalen. De motorgebruiker moet zelf routinematige inspecties, conditiebewaking en diagnostische methodes gebruiken om de motorconditie te bepalen en tijdig het benodigde onderhoud uit te voeren.

Een belangrijk onderdeel van het onderhoudsproces is volledige revisie. Tijdens dit proces wordt de motor van de vleugel gehaald, grotendeels ontmanteld, schoongemaakt, geïnspecteerd, daar waar nodig gerepareerd en uiteindelijk getest. Gedetailleerde kennis van de motorconditie vóór de revisie stelt de motorgebruiker en de werkplaats instaat alleen het onderhoud dat werkelijk nodig is in te plannen. De kennis van de motorconditie is daardoor belangrijk voor een kosteneffectief onderhoudsproces.

Conditiebewakingstechnieken kunnen zowel tijdens een motortest als tijdens de vlucht worden gebruikt. Traditionele technieken kunnen de conditie van de motor als geheel bepalen, maar zijn niet in staat om de conditie van de individuele gaspadcomponenten te bepalen. Door het complete gaspad met meer detail te analyseren kan de werkelijke conditie op componentniveau worden bepaald.

Het doel van dit onderzoek was het minimaliseren van beperkingen die zich voordoen bij het gebruik van gaspadanalyse in het onderhoudsproces van vliegtuigmotoren. Gaspadanalyse (GPA) is een diagnosemethode die in staat is om motormodules die de aero-thermodynamische motorprestatie verslechteren

te identificeren zonder dat de motor van de vleugel moet worden verwijderd of ontmanteld. Deze methode relateert variaties van motorprestatieparameters als gevolg van slijtage aan de conditie van de gaspadcomponenten. In de oude generatie gaspadanalysemethodes werden de relaties tussen de motorprestatieparameters en conditieparameters gelineariseerd waardoor deze onvoldoende nauwkeurig waren voor een effectieve toepassing in het onderhoudsproces. De ontwikkelingen in gasturbinesimulatiesoftware, numeriekemethodes en de rekenkracht van computers hebben geleid tot nauwkeurigere GPA-methodes die in twee categorieën kunnen worden onderverdeeld: empirische GPA-methodes en model-gebaseerde GPA-methodes. Empirische methodes maken gebruik van metingen verkregen van echte motoren en experimenten om de benodigde relaties te bepalen tussen de conditie van de motor en gemeten prestatieparameters. De inverse van deze relaties wordt dan gebruikt om de motorconditie te bepalen op basis van gemeten prestatieparameters. De model-gebaseerde methodes gebruiken de thermodynamische behoudswetten om gemeten prestatieparameters te koppelen aan de conditie van gaspadcomponenten. Hoewel de empirische en op model-gebasserde GPA-methodes veel verschillen, zijn alle GPA-methodes afhankelijk van zowel voldoende gemeten prestatieparameters en nauwkeurige kennis van de relaties tussen de gemeten prestatieparameters en conditieparameters om nauwkeurige resultaten te behalen. Door de beperkte beschikbaarheid van gemeten prestatieparameters, onvoldoende nauwkeurige GPA-programma's en het ontbreken van geïtegreerde informatiesystemen wordt GPA in de praktijk niet of inefficiënt toegepast in het onderhoudsproces.

Dit onderzoek is gericht op drie onderwerpen. Ten eerste, verbetering van de nauwkeurigheid en betrouwbaarheid van een niet-linear, model-gebaseerd GPA-programma. Ten tweede, effectiever gebruik maken van beschikbare motorprestatiegegevens voor GPA. Ten derde, het ontwikkelen van een informatiesysteemconcept voor GPA-toepassing in het motoronderhoudsproces. Dit onderzoek is gedaan door gebruik te maken van zowel simulatiedata als van prestatieparameters gemeten tijdens motortesten en tijdens het vliegen. Simulatiedata werden verkregen met behulp van het 'Gas turbine Simulation Program' (GSP). Dit is een simulatieprogramma waarin een gasturbine modulair kan worden opgebouw uit een bibliotheek van beschikbare componentsubmodellen die gaspadcomponenten, mechanischecomponenten of motorregelingcomponenten kunnen simuleren. GSP heeft ook een generieke *adaptive modeling* functie dat gebruikt kan worden voor model-gebaseerd GPA.

Het eerste belangrijke onderdeel van dit onderzoek was het verbeteren van de nauwkeurigheid en de betrouwbaarheid van model-gebaseerde GPA-resultaten. Hoewel de conditieparameters van gaspadcomponenten vanuit een motorprestatieperspectief niet direct gemeten kunnen worden, kunnen ze wel worden gemodelleerd. Daarentegen kunnen de effecten van conditieveranderingen in het gaspad wel worden waargenomen als veranderingen in motorprestatieparameters. GPA-programma's berekenen de afwijkingen van motorconditieparameters ten opzichte van een referentiemotor. Model-gebaseerde GPA-program-ma's bepalen deze afwijkingen door gasturbineprestatiemodellen te gebruiken. Twee effecten die de nauwkeurigheid van model-gebaseerde GPA-resultaten beïnvloeden zijn de nauwkeurigheid van het motormodel en de keuze van de referentiemotor.

Gasturbineprestatiemodellen maken gebruik van de thermodynamische behoudswetten om de interactie tussen de gaspadcomponenten te simuleren. Om het gedrag van de individuele gaspadcomponenten te simuleren onder verschillende operationele condities worden zogenaamde *component maps* gebruikt. Omdat de *component maps* het gedrag beschrijven van de werkelijke gaspadcomponenten, is de nauwkeurigheid van een gasturbineprestatiemodel sterk afhankelijk van de nauwkeurigheid van de *component maps*. Vliegtuigmotorfabrikanten beschouwen deze gedetailleerde informatie echter als bedrijfseigendom waardoor de benodigde *component maps* voor nauwkeurige motorsimulatiemodellen nagenoeg niet beschikbaar zijn buiten het bedrijf.

Om toch gasturbineprestatiemodellen te bouwen worden *component maps* die wel beschikbaar zijn in het publieke domein geschaald zodat ze het gedrag van het betreffende gaspadcomponent voldoende nauwkeurig beschrijven. In veel gevallen worden *component maps* geschaald ten opzicht van slechts één bedrijfspunt. Het resultaat is daardoor in veel gevallen onvoldoende nauwkeurig voor GPA-toepassingen. Om deze beperking te omzeilen is een *component map*-afstellingsmethode onderzocht die gebruik maakt van een grote hoeveelheid motorprestatiedata van recent onderhouden motoren gemeten tijdens de vlucht. Door gebruik te maken van veel motorprestatiemetingen over een ruime bandbreedte van motorbedrijfspunten kunnen de beschikbare *component maps* met meer detail worden afgesteld dan veelgebruikte schalingsmethodes. Deze aangepaste *component maps* beschrijven het gedrag van de werkelijke gaspadcomponenten nauwkeuriger wat tot betere GPA-resultaten leidt.

Andere verbeteringen van de nauwkeurigheid en betrouwbaarheid van GPA werden behaald door gebruik te maken van meerdere referentiemotoren om de conditie van een motor te bepalen. Operationele motoren kunnen ook dienen als referentiemotor. Doordat operationele motoren met een goede conditie onderling ook significante verschillen vertonen in conditieparameters, is het kiezen van de juiste motor belangrijk voor het verkrijgen van betrouwbare GPA-resultaten. Omdat iedere motor een andere onderhouds- en gebruikshistorie heeft, is de globale motorconditie als enige selectiecriterium voor een referentiemotor onvoldoende. Door meerdere referentiemotoren te gebruiken bij het bepalen van de conditie van een motor kan de onderlinge componentconditievariatie van de referentiemotoren in acht worden genomen. Dit leidt tot betrouwbaardere GPA-resultaten. Hoewel de berekende gaspadconditieparameters ten opzicht van iedere referentiemotor enigszins zullen verschillen, kan de variatie bij het gebruiken van meerdere referentiemotoren de onzekerheid van de GPA-resultaten zichtbaar maken.

Het tweede belangrijke onderdeel van dit onderzoek was de ontwikkeling van methodes om beter gebruik te maken van GPA in het vliegtuigmotoronderhoudsproces. Door middel van prestatietesten die onder gecontroleerde omstandigheden op een testbank worden uitgevoerd kan de werking van een vliegtuimotor in detail worden geanalyseerd. Hoewel deze testen verplicht zijn na een revisie, worden ze vanwege de benodigde voorbereidingstijd en kosten zelden uitgevoerd vóór motorrevisie. Hierdoor worden onderhoudswerkzaamheden voor motorrevisie vaak gepland zonder gedetailleerde informatie over de werkelijke conditie van de gaspadcomponenten. Omdat de effiënte werking van een gasturbine het resultaat is van een nauwkeurig op elkaar afgestelde interactie van de gaspadcomponenten, is de informatie over hun conditie essentieel voor effectief onderhoud. Een alternatief voor het verkrijgen van motorprestatiedata door deze te testen op een testbank is het gebruiken van motorprestatiedata gemeten tijdens de vlucht. Door deze zogenaamde *on-wing*data te gebruiken voor GPA kan de motorconditie nauwkeuriger in de gaten worden gehouden tijdens de vlucht en is de gaspadconditie bekend voor motorrevisie tegen minimale extra tijd en kosten.

Het derde belangrijke onderdeel van dit onderzoek was de ontwikkeling van een informatiesysteemconcept voor GPA-toepassing in het onderhoudsproces. Een relationele database, met daarin motorprestatiedata en informatie over het onderhoudsproces vormde een essentieel onderdeel. Deze database werd gekoppeld aan GSP GPA-tool en is gebruikt om de toegevoegde waarde van het systematisch gebruiken van GPA in het vliegtuigmotoronderhoudsproces te demonstreren.

Dit onderzoek heeft geleid tot de ontwikkeling van nieuwe methodes die in GSP zijn geïmplementeerd. De toegevoegde waarde is gedemonstreerd met behulp van een grote vloot turbofanmotoren. Er is veel concurrentie in de wereld van gasturbineonderhoud, reparatie en revisie. Systematisch gebruik maken van nauwkeurigere conditiebewakingsmethodes en diagnostische tools is nodig om een technologisch voorsprong te behouden ten opzicht van concurrenten die in staat zijn om vergelijkbare onderhoudsdiensten te leveren tegen lagere kosten. De ontwikkelingen die in dit onderzoek zijn beschreven zijn een stap richting het systematische gebruik van GPA in het onderhoudsproces van vliegtuigmotoren en helpen daarbij om de veiligheid, betrouwbaarheid en kosten-effectiviteit van luchtvaartmaatschappijen te verbeteren.

Contents

CHAPTER 1

Introduction

Gas turbine engines play an important role in aviation and power generation. Continuous development since the introduction of the gas turbine by Sir Frank Whittle have resulted in today's powerful and efficient engines which dominate the aircraft propulsion industry [36]. Jet propulsion enabled much faster and more efficient transport of larger aircraft over longer distances than propeller propulsion driven by piston engines. These developments made air transport financially accessible to the general public and led to a significant growth of the aviation market. In addition, the high thermal efficiency of gas turbines in a combined heat and power cycle configuration (CHP) makes these machines attractive for electric power generation. Microturbines are another promising application of the gas turbine engine. These miniaturized gas turbine engines may become widespread in distributed power and CHP applications as well as being a promising technology for powering hybrid electric vehicles.

The first gas turbine configuration used for aircraft propulsion was the turbojet engine. In this configuration all air that enters the engine inlet is expelled in a single high-velocity, high-temperature exhaust jet. Advances in gas turbine engine technology have resulted in several engine configurations for different aero-engine applications. The turbofan engine, which powers the majority of all commercial aircraft, is the most common gas turbine engine. The turbofan is essentially a turbojet with a large fan in the front and an extra turbine in the back. In this configuration some of the air that enters the engine via the fan passes through its core where it is further compressed, combusted and expanded before being expelled as a high-velocity jet. The rest of the air only passes through the fan and bypasses the core engine before being expelled at a slightly higher velocity. Because the addition of the fan increases the thrust significantly while requiring only a small amount of extra fuel compared to the fuel used by the core engine, the turbofan is a very fuel efficient engine.

Safety, reliability and cost-effective operation are essential for aero-engine applications. While the level of safety perceived by the public determines whether people will fly with a certain aircraft, engine reliability and cost-effective operation affect flight operations. A good example how engine reliability affects flight operations is the introduction of Extended Operations, better known as ETOPS[1]. When it was introduced, this rule allowed twin-engine aircraft to fly long-distance routes over water that previously required aircraft with more than two engines for additional reliability in case of engine failure. This way, improvements in turbofan reliability have contributed to more direct routes available for these twin-engine aircraft. Among other benefits, fewer engines reduced weight, fuel consumption and maintenance cost.

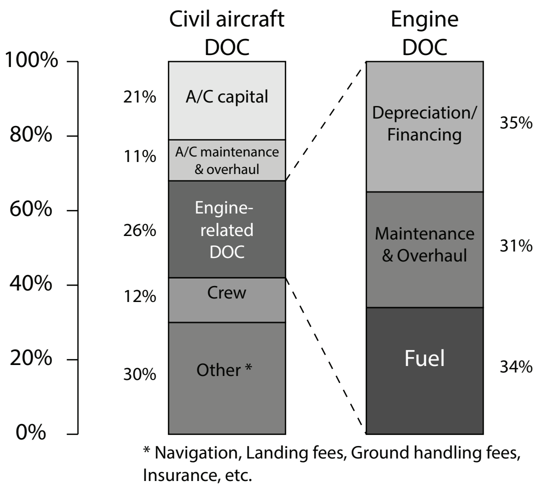
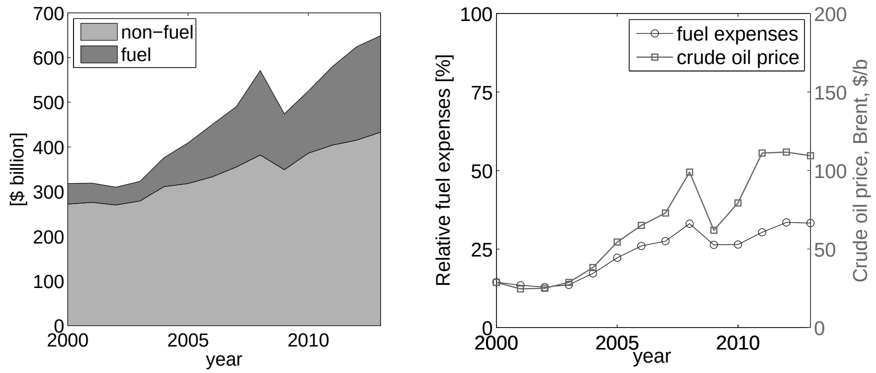


Figure 1.1: *Typical direct operating cost breakdown of a commercial aircraft powered by turbofan engines. This figure gives an indication of the cost fraction of fuel, maintenance, and financing for a modern turbofan engine in relation to the DOC of an aircraft. Source: Marinai et al. [42]*

Gas turbines are expensive to operate. The costs of supplying airline services are an essential input to many decisions taken by airline operators. The method of operational cost breakdown used by airline operators depends on the information that is necessary for decision support. Figure 1.1 shows an example of the direct operating cost (DOC) breakdown of a commercial aircraft with turbofan engines. Although the exact DOC breakdown fractions are affected by several factors including aircraft usage and the number of installed engines, the figure shows the relative importance of fuel and maintenance costs compared to other cost components. In figure 1.1 maintenance and fuel account for roughly 8% and 9% of the total aircraft DOCs. Cost reduction, often focused on maintenance cost and fuel cost, have always been important innovation drivers in the gas turbine field.

Figure 1.2(a) shows the total fuel and non-fuel expenses of the International Air Transport Association (IATA) commercial airline members[1]. Whereas both fuel and non-fuel expenses have been increasing during the past decade, fuel expenses have risen faster. In fact, the fraction of fuel expenses in 2013 have doubled since the year 2000. Figure 1.2(b) shows that fuel expenses have increased from 15% in 2000 to more than 30% in 2012. This figure also shows the trend of the yearly average crude oil price for the same period. The close correlation between the relative fuel expenses and crude oil price indicates how the oil price has a direct impact on fuel expenses which have become the single largest expense of airline DOCs.



(a) Global airline expenses.   (b) Relative fuel expenses and oil price trends

Figure 1.2: *Global airline fuel and non-fuel expenses. Values for 2012 and 2013 are expected and forecasted respectively. Data source: IATA [22].*

Combined, the data in figures 1.1 and 1.2 show that engine DOC's are significantly affected by fuel expenses. Because airline operators cannot reduce crude oil price and because engine financing and depreciation are long term aspects that are bound by contracts, maintenance has been perceived as a major target for cost control in the aviation industry. From an operational cost perspective, effective maintenance is important for two reasons. First, it can partially compensate for the increasing fuel expenses by reducing maintenance-related DOC's, and second, it helps reduce fuel consumption by ensuring efficient engine operation. Efficient engines use less fuel and produce

[1]IATA represents some 240 airlines that comprise 84% of the total air traffic [22].

fewer emissions. This latter aspect is also important when considering global climate change to which man-made emissions appear to have considerable contribution.

1.1 Aero-engine deterioration

Efficient performance of gas turbine engines is the result of a carefully tuned interaction among the compressors, combustors, and turbines; commonly referred to as *gas path components*. Figure 1.3 shows the configuration of gas path components of a typical two-shaft turbofan engine. In this configuration the fan and booster are driven by the low pressure turbine (LPT), and the high pressure compressor (HPC) is driven by the high pressure turbine (HPT). The latter two components combined are often referred to as the *core engine*. The airflow passing all turbomachinery components is referred to as the core flow and the air passing only the fan is called the by-pass flow. In modern turbofan engines used in civil aviation most of the thrust, around 80%, is generated by the cold by-pass flow. The remainder is generated by the hot core exhaust flow. The air mass flow ratio of by-pass flow to core flow affects the propulsive efficiency and the noise generated by the engine's exhaust. The purpose of the core engine is to generate the required gas power that the LPT converts into mechanical power for driving the fan.

During operation gas path components are susceptible to a variety of physical problems. These include problems such as fouling, erosion, corrosion, foreign or domestic object damage, tip clearance increase, worn seals, combustor damage, and many others [55]. These physical problems have the tendency to change surface quality, aerodynamic shape, flow patterns and pressure gradients. When present, they reduce the component's ability to function efficiently, thereby affecting gas path component interaction and lead to degraded engine performance. Because component deterioration also reduces the ability to withstand the loads that gas path components are subjected to, it affects engine safety, reliability and cost-effective operation.

1.1.1 Mechanical deterioration

During operation gas turbine components are subjected to various loads such as centrifugal, thermal, vibration, and pressure loads. Most of these loads have a repetitive nature because they originate from engine start-stop cycles, engine power setting changes, small rotating unbalances and other repetitive sources. If the repeated loads are above a certain threshold they can lead to fatigue damage. This damage mechanism initiates as small (micro) cracks in components that grow with each loading cycle. When not detected in time, these cracks may lead to catastrophic component failure.

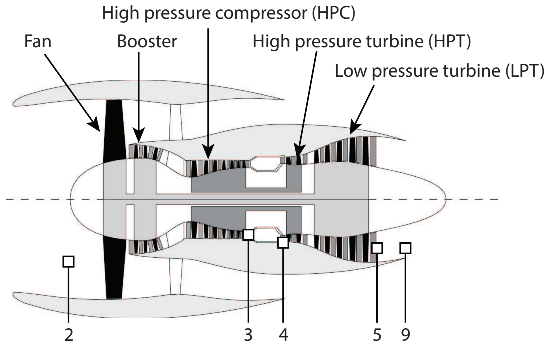


Figure 1.3: *Engine configuration of a typical two-shaft turbofan engine. The numbers indicate the standard gas turbine station numbers and relate to the temperature-entropy diagrams shown in figure 1.4.*

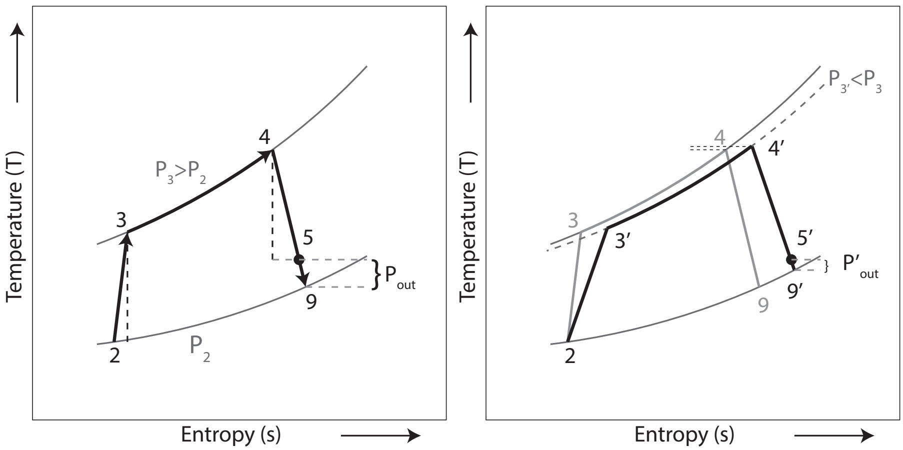
Fatigue damage is classified as either *low cycle fatigue* (LCF) or *high cycle fatigue* (HCF). Depending on the magnitude and nature of the repetitive load, component design, and material properties, failure resulting from LCF may occur in the range of 10^3 and 10^6 cycles. This translates to possible failure in terms of months or years. In gas turbines, the main source of LCF is the engine's start-stop cycle, which induces repetitive thermal loads. The main source that may lead to HCF are vibrational loads resulting from rotating mass unbalance or rapid pressure fluctuations across airfoils. Failure occurs typically in the range of 10^6 and 10^9 cycles. Because of the high frequency of vibrational loads that induce HCF the time between crack initiation and component failure may be very short; sometimes a matter of minutes. Although careful structural design can minimize unwanted vibrations, HCF is often initiated by external factors such as foreign or domestic object damage that cause mass unbalances and pressure fluctuations.

Another type of mechanical deterioration is creep: a slow, high-temperature deformation process during which parts undergo plastic deformation. Turbine blades are exposed to a combination of high temperatures and high centrifugal loads for extended periods during engine operation. This may lead to creep damage. At high temperatures, this deterioration process is very sensitive to temperature changes. When not detected in time, creep may also lead to component failure.

While fatigue and creep are examples of mechanical deterioration that affect gas turbine safety and reliability, their effect on engine thermodynamic performance, if any at all, is much smaller than other degradation mechanisms. Material deposits caused by fouling and changes to the airfoil geometry and surface finish caused by erosion and corrosion alter the aerodynamic performance of gas path components. Consequently, these deterioration mechanism are more likely to have a larger effect on engine performance compared to the aforementioned deterioration mechanisms.

1.1.2 Performance deterioration

From a thermodynamic perspective the effects of performance deterioration can be explained using the temperature entropy diagram, commonly referred to as the *T-s diagram*. This diagram is used in thermodynamics to visualize the changes in temperature (T) and specific entropy (s) of a fluid during a thermodynamic cycle. The curved lines in the T-s diagram are isobars, i.e., lines of constant pressure. The T-s diagram in figure 1.4(a) shows the open Brayton cycle that represents the idealized thermodynamic cycle occurring in gas turbine engines.



(a) Healthy performance. (b) Degraded performance

Figure 1.4: *Temperature-entropy (T-s) diagrams showing the thermodynamic gas turbine cycle. Figure 1.4(a) shows healthy engine performance and the direction of the thermodynamic cycle, and figure 1.4(b) shows the effects of degraded engine performance, which leads to reduced power output (P'_{out}).*

The Brayton cycle in its ideal form consists of two isobaric (constant pressure) processes and two isentropic (constant entropy) processes. The real thermodynamic process in a gas turbine engine is neither isobaric nor isentropic; the specific entropy increases during compression and expansion and pressure loss occurs during combustion. The numbers in these figures correspond to the gas path stations that are shown in figure 1.3. When the thermodynamic effects of the engine inlet are neglected, air entering the cycle at station 2 is compressed from pressure P_2 to P_3. Combustion at nearly constant pressure raises the temperature from T_3 at station 3 to T_4 at station 4. Expansion in the turbine reduces the pressure from P_4 at station 4 to P_5 at station 5 where it further expands in the exhaust nozzle and leaves the cycle at station 9.

Gas turbines generate a net power output because the hot gas expansion from the pressure at station 4 to station 9 delivers more power than necessary for compression of the cold air from the pressure at station 2 to station 3. This phenomenon is the result of the divergent isobars of the T-s diagram. The required compression power, indicated by the black, vertical dashed lines in figure 1.4(a), is the same as the expansion power extracted between station 4 and station 5. The remaining expansion power from station 5 to station 9 is converted to shaft power in a turboshaft configuration or to jet power in turbojet or turbofan configurations.

Effects of gas path component deterioration

The effects of gas path component deterioration can be explained by means of a T-s diagram. Deterioration reduces the ability of gas path components to perform their function. For example, a deteriorated compressor operating at fixed rotational speed (RPM) may deliver compressed air at slightly higher temperature but lower pressure ($P_{3'}$) compared to the same compressor with no deterioration operating at the same operating conditions. This is shown in figure 1.4(b) at station 3'. This results in a slight increase of required compression power compared to the original Brayton cycle. A fixed temperature increase during combustion leads to a higher turbine inlet temperature at station 4'. Because of the slightly lower compressor delivery pressure, less power can be extracted from expansion between 4' and 9'. Combined, the increased compression power and the reduced expansion power lead to reduced net output power from P_{out} to P'_{out}.

Because an aircraft requires a certain amount of thrust to perform its function, turbofan engines are equipped with a control system which ensures that for each power setting the desired thrust is generated despite the effects of component deterioration. To compensate for the effects of deterioration, the control system increases the fuel until the required thrust is generated. How the engine reacts depends on the control logic, engine limits and the levels of deterioration of each gas path component. In general the effects of deterioration are often (but not always) increased core engine speed, changes in pressure ratios, increased gas path temperatures and fuel consumption. Increased gas path temperatures combined with increased centrifugal loading resulting from increased rotational speeds may also accelerate some deterioration mechanisms such as creep and hot corrosion. These, in turn, change the geometry of gas path components and thereby affect their performance. This description shows that gas path component deterioration is a complex process where physical deterioration mechanisms and the resulting changes in engine performance mutually affect each other; always in an unwanted manner.

1.2 Aero-engine maintenance

Maintenance is necessary to restore the effects of mechanical and aero-thermodynamic performance deterioration. Because maintenance has such an impact on an aircraft's DOC, as suggested by figure 1.1, it has always been an important target for improvements. Over time, this has resulted in several maintenance strategies [59] that may be categorized as: *reactive*, *preventive*, and *condition-based* maintenance. These strategies have evolved over time with increasing operational experience and knowledge about component deterioration and material properties, development of new inspection methods and diagnostic tools, and requirements for cost-effective airline operations. However, all approaches have their own set of advantages and disadvantages.

Using a reactive maintenance strategy means that maintenance is applied after failure occurs. Although this strategy maintains high output levels until failure occurs, it is not always desirable. Failure may occur at an inconvenient time and place, and it may result in additional damage to components that may otherwise have been in good condition. These added circumstances always lead to unnecessary inconvenience and additional cost.

Cost-effective maintenance can be achieved by balancing maintenance cost on one hand and engine safety, reliability and availability on the other hand. While reactive maintenance maximizes an engine's operational hours, it ultimately leads to suboptimal safety, reliability, and availability. An approach for reducing unexpected failure and improving engine safety and reliability is applying preventive maintenance. This approach is based on the prediction of the average lifespan of components and the inspection, repair or replacement of those components before the end of their lifespan. Because components do not always fail at regular intervals, however, this strategy does not yield the maximum possible reliability and availability. The following three problems may lead to suboptimal preventive maintenance [15].

- *Unexpected failure*; component failure may occur between maintenance sessions.
- *Unnecessary maintenance*; good components might be disassembled and inspected. Moreover, in addition to unnecessary disassembly, the condition after reassembly might be worse than before overhaul.
- *Long overhaul*; because gas turbines consist of many small components, inspection of the large number of possible faulty components is time-consuming.

To minimize maintenance costs, a condition-based maintenance strategy can been employed. This strategy–also known as *on-condition maintenance*–uses no fixed intervals for engine removal. Instead, engine health is derived from condition monitoring techniques and inspections at pre-determined intervals. Maintenance is planned if there is proof of deterioration.

In practice, turbofan engine maintenance is based on a combination of preventive and condition-based maintenance [8, 55]. With this approach on-wing maintenance and engine removal are driven by gas path deterioration, physical deviations, usage of life-limited parts (LLPs) or other mechanical causes such as increased vibration levels. Because this approach leads to almost complete consumption of the service life of components, it may lead to significant cost-benefits compared to other methods. However, condition-based maintenance can only be used for components where signs of deterioration can be detected at an early stage. While condition-based maintenance offers substantial benefits for the maintenance process, unnecessary part replacements can still occur because in real aero-engine operations the maintenance intervals of preventive and condition-based maintenance do not necessarily line-up. For this reason much effort is put into developing effective diagnostic methods aimed at improving condition-based maintenance.

1.3 Condition monitoring and diagnostics

To detect and quantify the effects of mechanical and aero-thermodynamic performance deterioration diagnostic methods are used. Existing diagnostic methods may be grouped in four categories: mechanical integrity analysis, oil debris analysis, vibration analysis and performance analysis [15]. Information obtained through diagnostics is useful for engine removal planning and for estimating the required maintenance work scope.

Mechanical problems are generally identified through mechanical integrity analysis and oil debris analysis. Mechanical integrity ranges from external inspection of leaks, security of pipes, accessories, and control linkages to internal borescope inspection for detecting cracks, blade rubs, burns, deposits, and other signs of deterioration. Although very effective to identify and quantify the degree of deterioration, these diagnostic techniques are often time-consuming and require opening of covers, partial disassembly, specialized tools, and sometimes even engine removal to access the necessary engine components and parts.

For smooth operation of rotating gas turbine components their motion is restricted by rolling bearings and they are balanced with respect to their rotating axis. As bearings wear down and small mass imbalances develop due to non-axisymmetric deterioration in rotating gas turbine components, their vibration levels increase. Analyzing vibration patterns and identifying the root cause is called vibrational analysis. While in theory this diagnostic technique is very powerful, in practice it requires complex analysis. In addition, the available information regarding component vibration is limited to a few frequency filtered measurements. As a result of such limitations, only basic vibration analysis is used for monitoring vibration amplitudes at specific frequencies and warn when limits are exceeded. Upon exceeding vibration amplitude limits, visual inspection methods are used to locate the root cause.

1.3.1 Gas path analysis

Although the diagnostic techniques mentioned so far enable estimating an engine's mechanical state, they provide no information regarding its aero- thermodynamic performance. Gas turbine performance is determined by the performance of its gas path components and their interaction. Performance-related problems can be detected by measuring and monitoring parameters along the gas path such as pressures and temperatures. Since the objective of gas turbine maintenance is to restore engine performance and ensure safe, reliable, and cost-effective operation, and because maintenance of gas path components is both time-consuming and expensive, performance diagnostics should be an integral part of the maintenance process.

However, the complex aero-thermodynamic interaction among gas path components makes it difficult to detect the root-cause of performance-related problems. Even though the effects of gas path component deterioration can be observed by monitoring measured performance parameters, these parameters are also affected by changes in power setting and operational conditions, and by measurement error. Moreover, when comparing performance of different engines of the same make and model, small differences among engines may also lead to notable variations in measured performance parameters. Because all these factors occur simultaneously, reliably identifying the underlying root cause is difficult and usually impossible without additional analysis.

Gas path analysis (GPA) is a method that relates variations of measured engine performance parameters resulting from engine deterioration to the condition of its gas path components [60, 67, 68, 74]. GPA is a useful addition to existing gas turbine diagnostic methods that are used for condition-based maintenance. It enables component-level condition analysis without the necessity of engine disassembly, provides diagnostic information that cannot be obtained with other techniques, and provides more detailed information than existing performance monitoring techniques. These benefits may lead to substantial maintenance cost reduction. When used systematically in the aero-engine maintenance process, GPA offers substantial potential for anticipating the need of maintenance and guide the work scope definition process.

1.4 Experience with GPA so far

Developments in the field of GPA by the original equipment manufacturers (OEMs) in the late 70's and early 80's led to commercial GPA tools such as TEMPER [13] and COMPASS [53]. However, the accuracy and reliability of these tools was limited because of the linear approximation methods used for gas path diagnostics at that time as well as other factors such as measurement uncertainty and engine-to-engine differences. As a result, improving diagnostic accuracy has been the focal point for developing better GPA techniques [24, 38, 42]. This has led to many new GPA methods of which some directly use performance models and are referred to as *model-based GPA* or *differential GPA* [13, 53, 61, 62, 74], whereas others use *machine-learning* techniques in combination with large volumes of performance data and are referred to as *empirical GPA* or *artificial intelligence based GPA* [14, 29, 49, 77].

Despite the useful diagnostic capabilities and the improvements made in the past decades, GPA is not widely used in the aero-engine maintenance process or its application is limited to the analysis of performance data that are measured during mandatory performance acceptance tests after engine overhaul. While using GPA this way provides useful information when engines exhibit poor post-overhaul performance, it provides little added value to the overall maintenance process. The added value of GPA for the maintenance process can be further exploited when GPA is integrated in the maintenance process.

The limited use of GPA for aero-engine maintenance may be attributed to several factors of which diagnostic accuracy and reliability are two important ones. While developments in this field have led to more reliable and accurate techniques, no single GPA technique addresses all issues satisfactory [42]. For example, some methods are capable of accurately quantifying component condition deviations but need to know which component is deteriorated. In practice, this information is not available. Other methods do not need this a-priori information but do require specific engine data that are proprietary to the engine manufacturer. Without such data the GPA tool may not properly consider all aspects that affect observed engine performance and lead to inaccurate component condition estimations.

Another factor that limits systematic use of GPA is the absence of generic GPA tools. Often GPA tools are developed and demonstrated for a specific engine type and an available set of measured performance parameters. As a result, GPA tools may not be capable of analyzing multiple engine types. Gas turbine operators and engine shops usually work with multiple engine types, each of which may have different sets of measured performance parameters. Modifying an existing tool for different engine types and measured data set may not be possible or may require too much time and money. From that perspective generic GPA tools offer a significant advantage over engine-specific tools for MRO shops.

Apart from engine-specific GPA solutions, the absence of an integrated and flexible information system as part of a GPA tool for storing and retrieving measured and analyzed data may be considered as another limitation. In practice, the performance data that are necessary for GPA may have multiple sources (in-flight or test cell), each of which may have a different format as well as a different set of measured performance parameters for different engine types. When all these possible variations require manual user actions they may have a discouraging effect for using a tool and potentially introduce errors. Therefore, integrating and systematically using GPA in an existing maintenance process requires an integrated and flexible information system.

Finally–and this may be considered as a strong argument against using GPA–poor engine performance is not always the primary reason for engine removal and overhaul. Life-limited parts and other mechanical problems also trigger engine removal. Gas turbine life-limited parts are those engine rotating and major static structural parts whose primary failure is likely to result in a hazardous engine effect and for which the operational life is limited to a total life counted in hours, cycles, landings, or by calendar. When LLPs trigger engine overhaul and GPA is not used in the condition-based strategy for assessing gas path condition, some gas path components might receive very limited maintenance based on component condition estimations obtained via other inspection methods. However, maintaining a gas turbine engine without knowing the condition of its gas path components may result in incorrect maintenance and poor performance after overhaul and cause the engine to fail its mandatory post-overhaul performance acceptance test. Thus, regardless of the removal reason of any gas turbine aero-engine, GPA should be an integral part of the maintenance process to ensure a cost-effective maintenance process.

1.5 Research scope and objectives

When considering practical limitations of existing gas path analysis methods and tools as well as current implementations of this diagnostic tool in the aero-engine maintenance process there still is room for improvement. The objective of the research work presented in this thesis is to study how GPA can be used more effectively in the aero-engine maintenance process and whether challenges that currently limit GPA can be overcome with available data and methods. The main research question addressed by this thesis is:

> *How can gas path analysis be more effectively used in the maintenance process of gas turbine aero-engines?*

The research and development challenge lies in improving the accuracy and reliability of GPA and achieving this by using only data available to gas turbine MRO shops rather than data from gas turbine manufacturers. Another important factor to more effectively use GPA in existing maintenance processes is to include a system that enables interaction between measured engine performance data, the maintenance process and a GPA tool.

The approach used in this work is to first identify the main challenges that limit systematic application of GPA in the maintenance process. This research project uses NLR's Gas turbine Simulation Program (GSP) [46], a component based performance simulation tool that can model virtually any gas turbine engine configuration [72]. An adaptive modeling (AM) capability was developed at Delft University of Technology that has been implemented in the generic component based simulation environment of GSP [73, 74]. This AM component has been in use as a technology demonstrator at KLM Engine Services since 2004 for post-overhaul gas path component diagnostics of the CF6-50, CF6-80, and CFM56-7B engine families.

When the main limitations are identified, the aim is to conceptually develop and implement the necessary improvements into the existing adaptive modeling component of GSP. The added benefits of systematically using GPA in the aero-engine maintenance process are demonstrated by using large volumes of measured performance data that were obtained from a fleet of gas turbine aero-engines. In addition, an information system is developed for better connecting available performance data to the AM tool.

The benefits of integrating gas path diagnostics in the aero-engine maintenance process may not be limited only to the aero-engine itself. Indeed, knowing the condition of gas path components before maintenance may help planning engine overhaul and determining what maintenance actions are necessary. Such an application of GPA will likely result in better post-overhaul performance. But by relating component condition information to maintenance actions, the effectiveness of the aero-engine maintenance process itself may be quantified.

This study attempts to develop knowledge applicable to any gas turbine engine operator by using a non-OEM GPA tool as well as engine performance data that would be available to engine operators. Although it is primarily focused on the GPA application for civil gas turbine aero-engine maintenance, the methods, results, and conclusions presented herein apply to maintenance of gas turbines in general. They are readily applicable to other gas turbine fields such as land-based power generation, marine, and military applications.

1.6 Thesis outline

This thesis is structured as follows.

- Chapter 2 describes the gas path analysis concept and how it is used for detecting gas path component deterioration. A comprehensive overview of existing GPA methods and latest developments are presented, including an assessment of their strengths and weaknesses. This chapter also describes in detail the GPA tool used for this research.

- Chapter 3 presents the investigation of the current GPA use in an aero-engine maintenance environment. While there are many challenges related to GPA, the wide range of GPA methods that exist today were mainly developed to address the mathematical inverse problem. From the available literature, it appears that the other challenges have received little attention. By analyzing the strengths and weaknesses of GPA in relation to the needs of aero-engine maintenance, an attempt is made to uncover hidden GPA potential and identify necessary improvements.

- Limited accuracy and unreliable performance parameter measurements are considered a major obstacle in systematically using GPA. Chapter 4 presents the methods for improving accuracy of model-based GPA and dealing with measurement uncertainty.

- Chapter 5 is concerned with the application of the enhanced GPA tool to aero-engine maintenance process. It synthesizes the work presented in chapters 3 and 4 and demonstrates how the added potential of GPA can be beneficial to the aero-engine maintenance process. The focus is both on post-overhaul test cell engine diagnostics as well as on-wing component condition monitoring. Several case studies are used to demonstrate both applications.

- Although both accurate GPA tools as well as accurate performance data are necessary for reliable diagnostics of gas path components, effectively integrating GPA into the aero-engine maintenance process requires an information system: a system that enables interaction between engine performance data, performance engineers, maintenance process, and a GPA tool. Chapter 6 describes the requirements and necessary development steps for a dedicated GPA information system. Finally, chapter 7 presents concluding remarks.

CHAPTER 2

Gas path analysis

Abstract

Diagnostic tools are essential for effectively using the condition-based maintenance approach for gas turbine aero-engines. Gas path analysis (GPA) is a method that can isolate and quantify the relative severity of problems that affect engine performance. This chapter describes how measured performance parameters are used for detecting component deterioration. It provides a general overview of existing GPA methods that have been developed over the years and describes their strong and weak characteristics. The focus is on model-based GPA and the zero-dimensional performance modeling technique that form the basis of model-based GPA. This chapter also addresses the adaptive modeling technique that was used for GPA in this research as well as the Gas turbine Simulation Program GSP which has an embedded adaptive modeling capability.

FROM a thermodynamic perspective, efficient performance of gas turbine engines is the combined result of individual gas path component performance as well as their mechanical and aero-thermodynamic interaction. During their operational life gas path components are susceptible to various physical problems such as fouling, erosion, corrosion, partially damaged or missing blades, foreign or domestic object damage, tip clearance increase, worn seals, combustor damage, and many others. The deteriorated performance caused by these wear and tear mechanisms leads to a new but suboptimal equilibrium operating points among gas path components. While the exact behavior of a deteriorated engine depends on the type and severity of the deterioration and the components that are deteriorated, the bottom line is that a deteriorated gas turbine delivers less power for a certain amount fuel mass flow or requires more fuel to deliver a certain amount of power.

Changes to the condition of gas path components can be described in several ways. From a thermodynamic perspective the condition of gas path components is quantified in terms of isentropic efficiency (η), mass flow capacity (Wc) and pressure ratio (PR). The isentropic efficiency is defined as the ratio of work between the ideal process and real process that occur in the gas path components of a gas turbine engine. Using the concept of total specific enthalpy (h_t), the isentropic efficiency of a compressor and turbine in a gas turbine are described respectively as:

$$\eta_{compressor} = \frac{h_{t_{exit},is} - h_{t_{in}}}{h_{t_{exit}} - h_{t_{in}}} \tag{2.1}$$

$$\eta_{turbine} = \frac{h_{t_{in}} - h_{t_{exit}}}{h_{t_{in},is} - h_{t_{exit}}} \tag{2.2}$$

The mass flow capacity, or *flow capacity*, is the corrected mass flow passing through a gas path component. The corrected mass flow is defined as:

$$Wc = \frac{\dot{m}\sqrt{R \cdot T_{t_{in}}}}{P_{t_{in}} D^2} \tag{2.3}$$

It is the actual mass flow ($\dot{m}$) that is corrected for gas properties represented by the specific gas constant (R), thermodynamic state described by pressure and temperature (P and T), and a parameter representing the cross sectional flow area of that component (D).

The pressure ratio is the ratio between the inlet and exit pressure of a gas path component and is defined as:

$$PR = \frac{P_{exit}}{P_{in}} \tag{2.4}$$

The severity of component deterioration can be represented by the difference between the actual *component condition parameters* and their baseline values. This difference is referred to as the *condition delta* or *component condition deviation*. Large condition deltas represent more severe deterioration. Deterioration always results in reduced isentropic efficiency of any gas path component but it may lead to increased or decreased mass flow capacity and pressure ratios. Even though the effects of gas path component deterioration may be quantified this way, these component condition parameters cannot be measured directly. Instead the effects of component deterioration can produce observable changes to measurable performance parameters such as pressure, temperature and rotational speeds. By analyzing the changes to the measurable performance parameters while taking into account the effects engine operating conditions and power settings, the presence of component deterioration can be implicitly detected. This technique is referred to as gas path analysis.

2.1 The GPA concept

Figure 2.1 shows a schematic of the relation between physical degradation mechanisms, independent component condition parameters, and dependent and observable engine performance parameters. The relation shown in this figure can be used in several ways. One widely applied method that makes use of this relation is *gas path performance monitoring*. These systems enable monitoring of measured performance parameters and calculated parameter groups. For each monitored parameter thresholds can be specified. Parameter threshold exceedances may lead to maintenance actions to further investigate or solve a potential problem. Even though these systems can detect the effects of changed component condition on engine level by observing gas path performance parameters such as fuel flow, temperatures, pressures, rotor speeds, or others, they are unable to quantify the independent component condition parameter changes.

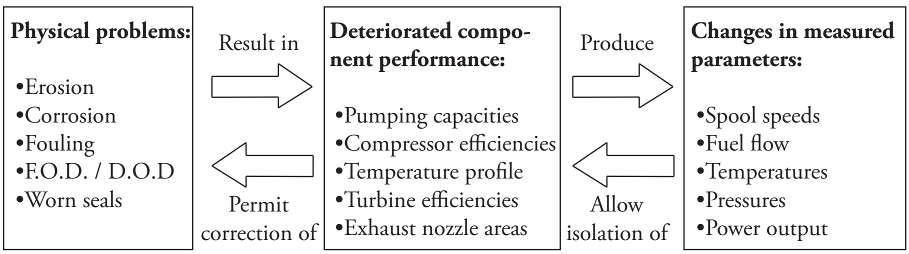


Figure 2.1: *Relation between physical degradation mechanisms, component condition changes, and observable engine performance parameters. Source: [67]*

Because gas path component deterioration also affects component interaction, the effect of deterioration is usually observed by simultaneous changes to several performance parameters [67]. In addition, these effects are further complicated because gradual component deterioration usually occurs simultaneously in multiple components. Because changes in power setting and atmospheric conditions at the engine inlet also affect engine performance parameters identifying the root cause of the degraded engine performance requires additional analysis.

Another way to exploit the relation shown in figure 2.1 is by means of *differential gas path analysis*. This method uses computer models for relating measured engine performance parameters to component condition parameters. It attempts to identify component condition deviations by comparing observed performance parameters to baseline engine performance and using either the known underlying thermodynamic relations or known fault signatures.

The objective of a practical differential GPA tool is to detect as many of the physical gas path problems as possible by means of available measured engine performance parameters. Problems such fatigue cracks in the rotor disks or blades, corrosion that only affects the metallurgical characteristics, or a mass imbalance resulting in excessive vibrations may not be detected with this technique and require other diagnostic methods. While some problems have a purely mechanical origin and do not affect engine performance, many have a direct effect on engine performance and are best diagnosed using performance measurements [41]. Therefore, cost-effective gas turbine maintenance requires an integrated approach in which GPA is used together with other diagnostic techniques [67].

Apart from the complex interaction between measurable performance parameters and component condition parameters mentioned so far, the accuracy of any GPA technique is also affected by measurement uncertainty, the availability of measured performance parameters and the accuracy of the GPA technique itself. Attempting to overcome these challenges has led to the development of several GPA methods that can be classified as either *model-based GPA methods* or *empirical GPA methods*. Before these methods are further characterized in section 2.3, the basic concepts of gas turbine performance modeling are discussed.

2.2 Gas turbine performance modeling

Gas turbine performance models are used in almost all phases of the gas turbine life cycle. Performance modeling can be divided in two categories: *design point* performance modeling and *off-design* performance modeling [47].

Design point performance modeling is used for optimizing engine configuration, component design, and cycle parameters such that the required overall engine performance is met at specific operating conditions. For aero-engines the fitness of a design is assessed by characterizing engine performance parameters such as net thrust, specific thrust, and specific fuel consumption. Every change to the input parameters during this calculation procedure requires a different engine geometry at a fixed operating condition. Basic cycle calculations, which are covered in detail in texts on gas turbine theory [57, 75], are used for design point performance analysis.

Once the geometry of all gas path components has been selected and the design of an engine is fixed, *off-design performance modeling* is used to determine whether the interaction among gas path components and the engine control system at different operating conditions results in satisfactory performance. When performance limitations are exceeded at this stage, off-design performance analysis can be used to determine which modifications are necessary to the engine design such that satisfactory performance is achieved. In addition to simulating *steady state* engine performance, off-design performance models can also include time-dependent processes such as component acceleration or deceleration thereby allowing for *transient* off-design engine performance analysis.

Spatial discretization, which may range from zero-dimensional (0-D) to full three-dimensional (3-D), is another aspect of off-design performance models. 0-D, or parametric, models are the most widely used for gas turbine performance analysis. These models do not use spatial discretization but instead calculate the averaged gas properties at discrete locations along the gas path. Individual gas path components such as compressors, combustion chamber, and turbines that form the engine are considered as a set of black boxes. This 0-D approach requires relatively simple calculation methods to solve a reduced number of unknowns for modeling [47]. 1-D performance models operate in a similar fashion, but usually apply a spatial discretization along the mean flow path which represents the average gas path trajectory from inlet to exhaust. Gas properties are also calculated along this mean flow path within each component. Even though this generates more detailed information than 0-D models, it requires more information to set up. 2-D and 3-D models increase the number spatial dimensions. While multi-dimensional model are capable of calculating gas properties in more detail, it requires detailed geometric data of all gas path components, which are hard to obtain, and a much higher computational load.

Because the objective of GPA is to estimate condition deviations on component level, additional spatial discretization is not necessary. GPA methods use 0-D, steady state performance models. Moreover, pressure and temperature sensors required for GPA are usually located along the gas path at the component interfaces, i.e., the location in the gas path where one component ends and another begins. Figure 2.2 shows an example of a typical twin-spool turbofan engine configuration including the major engine modules or components.

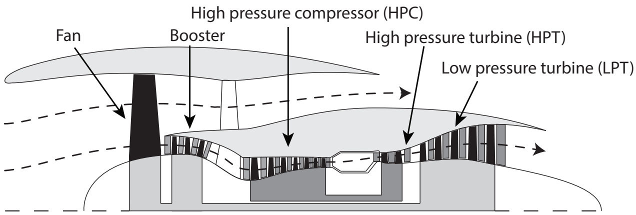


Figure 2.2: *Layout of a typical twin-spool turbofan engine. The dashed arrows indicate the bypass and core flow path.*

2.2.1 Component performance maps

On engine level, performance models simulate steady state off-design performance by using the laws of conservation of mass, energy, and momentum to obtain equilibrium operation among the gas path components of the gas turbine model. Off-design performance prediction on component level requires a different approach compared to performance prediction on engine level. For relatively simple gas path components such as inlet and exhaust components, fixed losses relative to design performance are sometimes used. Instead of solving the Navier-Stokes equations to estimate detailed fluid properties and deduce off-design component performance, 0-D performance models use *component maps* (or component characteristics) for estimating off-design performance of turbomachinery components such as compressors and turbines. The component maps, which are often in tabular form, describe component behavior in terms of corrected performance parameter groups. Estimating off-design performance of each gas path component in a performance model is achieved by interpolating the necessary component maps.

Performance of gas path components depend on the geometry, inlet conditions, and other design characteristics such as rotational velocity for rotating components. Turbomachinery component performance can be described by using 8 parameters [57]. For a compressor the following functional relation may be used for expressing its performance.

$$Compressor\,performance\ = f(D, N, m, P_{t1}, P_{t2}, RT_{t1}, RT_{t2}, \nu)$$

In this functional relation D is a characteristic linear dimension of the component, N its rotational speed, m the mass flow through the component, P the pressure, RT temperature, and ν the viscosity. The subscript *t1* and *t2* refer to total (or stagnation) inlet and outlet conditions respectively. The temperature T here is associated with the gas constant R such that the combined parameter RT has the dimensions of velocity squared. For modeling purposes, however, it is convenient to minimize the number of performance parameters required to describe component performance. This facilitates the numerical calculation and enables quick and easy analysis.

Dimensional analysis is used to reduce these 8 parameters down to the 5 non-dimensional parameter groups shown in the center column of table 2.1. This topic is covered extensively in other literature such as [25, 57, 75]. In general, non-dimensional parameter groups reflect the dynamic processes that occur in gas path components. For a specific engine configuration, the parameter groups can be normalized to ambient atmospheric conditions. These corrected parameters, shown in the right column of table 2.1, are not dimensionless. Because of this normalization, at standard conditions, the values for the corrected mass flow and shaft speed are identical to the actual values.

Strictly speaking the Reynolds number is required for full specification of component performance. It is a measure of the ratio of inertia forces to viscous forces and quantifies the relative importance of these two forces for given flow conditions [25]. The greatest effect of Reynolds number variations, as a result of altitude changes, is on component efficiency. However, performance effects due to Reynolds number variations are small and therefore neglected in most cases.

	Non-dimensional parameters	Corrected parameters
mass flow	$\frac{\dot{m}\sqrt{R \cdot T_{t1}}}{P_{t1} D^2}$	$\frac{\dot{m}\sqrt{\theta}}{\delta}$
shaft speed	$\frac{N \cdot D}{\sqrt{R \cdot T_{t1}}}$	$\frac{N}{\sqrt{\theta}}$
pressure ratio	$\frac{P_{t1}}{P_{t2}}$	$\frac{P_{t1}}{P_{t2}}$
efficiency	η	η
Reynolds number	$\frac{P_{t1} \cdot D}{\sqrt{R \cdot T_{t1}} \cdot \mu}$	$\frac{\delta \cdot D}{\sqrt{\theta} \cdot \mu}$

Table 2.1: *Non-dimensional and corrected parameters used for component performance where* $\theta = \frac{T}{T_{amb}}$ *and* $\delta = \frac{P}{P_{amb}}$.

The working medium in a specific gas turbine configuration is fixed. Therefore, the universal gas constant R, shown in the non-dimensional group of the mass flow and shaft rotational speed, is often omitted. If a specific compressor design is analyzed, the characteristic geometry D will remain constant and can therefore be omitted.

Component characteristics contain the correlation between these parameter groups that describe component performance in discrete tabular form. These tables are often shown graphically and are therefore commonly referred to as component maps. An example of a compressor map is shown in figure 2.3. Because of the relations between corrected parameter groups, any two parameter groups are sufficient for specifying the operating point of a component.

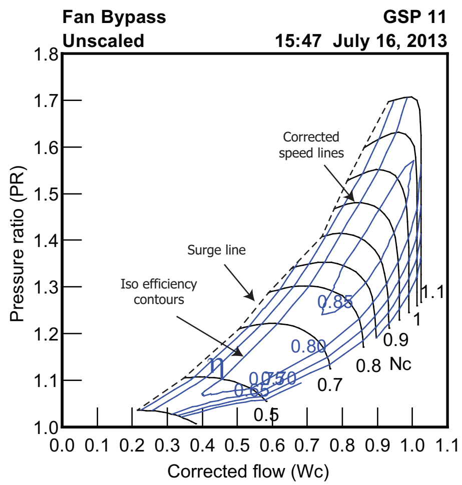


Figure 2.3: *An example of a compressor map. The figure shows the correlations between the corrected parameter groups that form the compressor map.*

Since engine performance depends on individual component performance, accurate component maps are key for obtaining correct off-design performance simulation results. While original component maps would be desirable, these are often proprietary and are usually not available outside the engine manufacturer's environment. Alternatively, component maps available for similar components are generally used instead [31]. Although for most gas path components the correlation between parameter groups are established experimentally, computational fluid dynamic tools or other methods are also used for estimating component maps [30, 33].

2.2.2 0-D component matching method in GSP

0-D performance modeling tools calculate valid steady state performance by iteratively solving the basic conservation equations and obtain equilibrium performance among all gas path components. Off-design component performance is estimated by interpolating the component maps of each gas path component.

To perform these calculation steps in GSP, the engine operating point is numerically represented by the model state vector. The operating state of a single component is defined by *state variables.* Because of physical connections and continuity requirements some components have common state variables. Examples are mass flow of adjacent gas path components and shaft rotational speed of components that are mechanically connected. The state variables together form a *state vector*, which contains all information to specify the model state and thus the engine operating point. Equation 2.5 shows an example of a state vector for a basic turbojet model that contains five gas path components and requires four state variables to specify the model state.

$$\bar{S} = \begin{bmatrix} s_1 \\ s_2 \\ s_3 \\ s_4 \end{bmatrix} = \begin{bmatrix} \frac{W}{W_{des}} \\ \frac{N}{N_{des}} \\ \frac{\beta_c}{\beta_{c\,des}} \\ \frac{\beta_t}{\beta_{t\,des}} \end{bmatrix} \tag{2.5}$$

Because the state variables represent values that may differ several orders of magnitude, they are normalized to avoid instability problems during the numerical iteration process. The variables in the state vector are normalized with respect to the model reference point performance levels. Therefore the state vector defines the model state relative to this reference point.

The conservation laws necessary for calculating a model state are established by defining error equations among the components. In other words, the error equations define the relations between the various component state variables of the gas turbine model. To have a fully determined system of equations an equal number of state variables and error equations is required. The error equations combined with the state variables form a set of non-linear differential equations.

$$E_i = \dot{m}_{inl} f(s_1) - \dot{m}_{comp} f(s_2, s_3) \tag{2.6}$$

An example of an error equation is shown in equation 2.6, where the mass flow through the inlet component, as a function of state variable s_1, is related to the mass flow through a compressor component, with state variables s_2 and s_3. This error equation represents the conservation of mass, since the air flow through the compressor component must first pass the inlet component. A non-zero error indicates a deviation from a physical relation between components and thus an invalid solution.

2.2.3 Iterative solution method

For a design point calculation, all design parameters such as mass flows and pressure ratios are defined and the engine model is sized to those parameters. This means that dimensions such as the nozzle throat area are fixed. At this point, all error equations are defined and the state variables are set to 1. An iterative solution method is used for calculating valid off-design operating points. Although the set of error equations, which define the model, may be solved separately through local iterative methods, the usual approach is simultaneously solving the set of equations with a multi-variable *Newton-Raphson* method [47]. The *Newton-Raphson* method is a numerical method capable of finding the roots of an arbitrary function. Apart from this iterative solution methodology for solving the system of equations, interpolation and extrapolation methods are necessary for estimating off-design component performance from discrete tabular data, and numerical integration methods are used for transient simulations.

Even though the Newton-Raphson method is often used for gas turbine performance calculations, it does have some weak points. For instance, starting from the same initial point will always lead to the same solution, i.e. the same root, even if there are multiple solutions. To find all roots, multiple starting points would be necessary. Another common problem is that of local minima. If a local minimum of a system of equations has a positive value, the Newton-Raphson method may get stuck in this minimum and will not converge to a solution. In practical applications of the Newton-Raphson method, corrective measures are taken to mitigate disadvantageous characteristics of this method. Discussing these measures is outside the scope of this thesis.

2.3 Gas path analysis methods

GPA is based on the analysis of measured performance parameter deviations relative to their nominal or baseline values. Because gas turbine performance depends on ambient condition, power setting, and component condition, a GPA tool should be able to differentiate between nominal performance variations, and performance deviations resulting from component deterioration. One way of realizing this capability is by using performance models that simulate steady state gas turbine behavior. With the *model-based* approach the effects of ambient condition and engine power setting on performance parameters can be included.

2.3.1 Model-based gas path analysis

In 1973 Louis Urban published an article [67] in which he introduced GPA as a method *'which permits the isolation of single or simultaneous multiple engine faults, with a quantitative assessment of their relative severity'*. The GPA method he suggested was an improvement on the *Fault Coefficient Matrix* (FCM) method that was more widely known at that time.

The FCM method statistically determined the most likely single fault by comparing measured performance parameters to tables that contained precalculated expected performance parameter deviations for various possible component condition deviations. Although the FCM method had demonstrated value when properly applied to single fault situations, its inability to handle multiple fault cases, which are more likely to develop in operational gas turbines, was a serious disadvantage. This stems from the fact that in gas turbines a limited set of measured performance parameters coupled to an extensive list of possible faults can often result in questionable interpretations. Moreover, a single fault may have virtually the same effect on measured performance parameters as multiple faults occurring simultaneously, and different sets of multiple faults may also have the same effect on measured performance parameters.

Instead of using precalculated relations in tabular form, the GPA method that Urban had introduced used a gas turbine performance model that was derived by using the basic laws of thermodynamics and variations of specific heats, as well as engine specific characteristics such as pressure losses, component maps, and nozzle flow coefficient and unchoking effects. In absence of measurement uncertainty a gas turbine engine may be mathematically described as follows:

$$\bar{p} = g(\bar{c}, \bar{o}) \tag{2.7}$$

In this equation the output vector $\bar{p}$, which represents the measured performance parameters, is a non-linear function $g()$ of the input vectors $\bar{c}$ and $\bar{o}$, which represent respectively component performance characteristics such as efficiencies and flow capacity, and engine operating conditions such as local atmospheric conditions and power setting. In presence of measurement uncertainty in the form of sensor noise and bias, equation 2.7 becomes:

$$\bar{p} = g(\bar{c}, \bar{u}) + \bar{b} + \bar{n} \tag{2.8}$$

where vectors $\bar{b}$ and $\bar{n}$ represent respectively sensor bias and sensor noise. Vector $\bar{u}$ represents the measured operating conditions, which is a combination of the true operating conditions $\bar{a}$ that are also affected by sensor noise and bias, i.e., $\bar{u} = \bar{a} + \bar{b}_a + \bar{n}_a$.

The differential GPA method that was introduced by Urban used a set of equations that were linearized at a given steady state operating point. This linearized set of equations can be expressed in matrix form as:

$$\Delta\bar{p} = \mathbf{G}\Delta\bar{c} \tag{2.9}$$

This equation relates component condition deviations ($\Delta\bar{c}$) to measurable performance parameter deviations ($\Delta\bar{p}$). Matrix $\mathbf{G}$ is often referred to as the influence coefficient matrix (ICM). For illustrative purposes, the effects of measurement uncertainty are omitted in this equation. Inverting this linearized system of equations leads to equation 2.10, which is the basic matrix equation for GPA. The inverse of the ICM, $\mathbf{G}'$, is often referred to as the fault coefficient matrix. If the ICM is invertible and the vector $\Delta\bar{p}$ is free of uncertainties, equation 2.10 directly relates measurable performance parameter changes to component condition changes.

$$\Delta\bar{c} = \mathbf{G}'\Delta\bar{p} \tag{2.10}$$

Linear model-based GPA applications have been described extensively in scientific publications [13, 15, 42, 53, 60, 67]. Apart from describing the basic method, several improvements, and its applications, these and other authors also emphasized some limitations that have sparked the development of other GPA methods that are described in this chapter.

To be invertible the ICM must be a square matrix [37]. In other words, the system of equations in 2.10 requires an equal number of component condition parameters and measured performance parameters. For many turbofan engines, limited measured performance parameters are available. Moreover, the measured performance parameters may not be sensitive to all condition parameters [28, 48, 68]. Both aspects may limit the number of component condition parameters that can be calculated for a given combination of engine configuration and measured parameters.

Because of measurement uncertainty, the vector $\Delta\bar{p}$ is not free of uncertainties. To handle the effects of measurement uncertainty, improvements were made to the basic GPA method by including techniques such as weighted-least-squares and Kalman filters. Although these improvements reduced the effects of measurement uncertainty, the GPA results were still not sufficiently reliable [38]. In some cases, the improved linear GPA methods introduced a *smearing* effect, where the root cause of measured performance deviation is distributed over multiple components.

This method is based on the assumption that a linear relation exists between condition parameters and performance parameters. In reality this is not the case and the accuracy of a linearized model-based GPA method is acceptable in a narrow range of performance parameter deviation for a specific ICM. Moreover, because deterioration of one gas path component may affect the performance of other gas path components, the ICM that was established for a specific operating point may not be valid.

Non-linear model-based GPA

To capture non-linear gas turbine behavior and improve GPA accuracy, non-linear model-based GPA methods have been developed. These GPA methods use similar principles as linear GPA. The main difference is the improved performance prediction accuracy at operating points different from a reference operating point. These differences are caused by variations in operating conditions and component deterioration. This effect is visualized in figure 2.4. Consequently, when non-linear performance models are used for GPA they often produce more accurate component condition estimations compared to linear models [26].

A technique that uses non-linear performance models for GPA is *Adaptive Modeling* [35, 61, 74]. This technique works by adapting a performance model until simulated performance parameters match measured performance param-

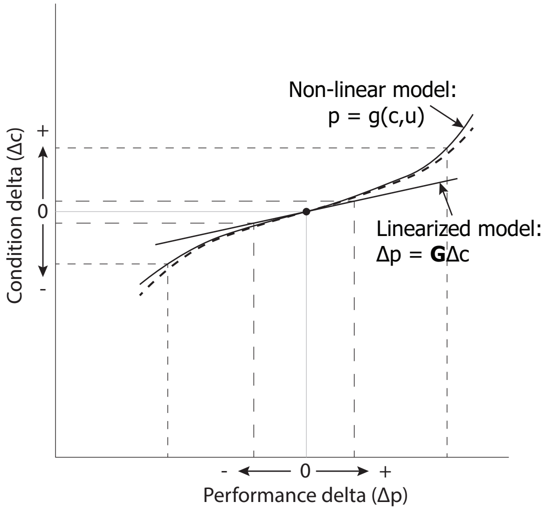


Figure 2.4: *Accuracy comparison of linear GPA to non-linear GPA. For increasing performance deltas, the modeling error of linear GPA methods increase to similar orders of magnitude as the condition delta they try to calculate. This effect is much smaller for non-linear GPA methods.*

eters. Model adaptation is realized by adapting the component performance characteristics. The degree of component adaptation necessary to match measured performance parameters gives an indication of the level of component deterioration.

The non-linear performance modeling method that is explained in section 2.2 uses component maps for simulating off-design component performance. This way, two component characteristic parameters are necessary for specifying any operating point in a component map, e.g., efficiency and corrected flow parameter values to specify a compressor operating point. As shown in figure 2.1, component deterioration affects those characteristic parameters. *Map modifiers* are used for scaling the component performance characteristics during the AM calculation. A map modifier (MM) is defined as the ratio of the adapted component characteristic value, which is necessary for matching the measured steady state operating point, and the reference component characteristic value [74]. Equation 2.11 shows the MM definition for compressor efficiency. In the AM process, MMs are defined for each component performance characteristic that is included in the calculation. The difference of a MM relative to its reference value of 1 is referred to as the *component condition deviation* or *condition delta*. For example, a condition deviation of +4% originates from a MM value of 1.04 which in turn means that the adapted component characteristic parameter value is 4% larger than its reference value.

$$MM_\eta = \frac{\eta_{adp}}{\eta_{ref}} \tag{2.11}$$

To add an adaptive modeling functionality to a performance model, additional equations are necessary for relating measured performance parameters to simulated performance parameters. Both equation sets may be solved simultaneously, thereby solving the model equations and model adaptations in one session. This requires additional terms are added to the existing performance model equations to ensure that the effects of adapted component characteristics are included in the basic performance model. Alternatively, the set of adaptation equations may be defined as a minimization problem where an objective function is solved iteratively with appropriate numerical methods. While both approaches may lead to the same solution, the latter requires additional calculation loops to ensure that adaptations to the model characteristics are taken into account in the basic model equations.

2.3.2 Empirical gas path analysis methods

Numerical solvers used for model-based GPA methods often lead to rapid convergence. However, occasionally a solution may not converge. Convergence problems are often caused by derivation problems of ill-conditioned matrices or relative extrema in the solution space. While precautions can be taken to mitigate those problems, they are not always effective for every situation. Another effect that influences GPA results is measurement uncertainty. It tends to obscure the otherwise predictable effects of ambient conditions, engine power setting, and component deterioration on engine performance. As a result, it makes diagnosing condition deviations more difficult.

Gas turbine performance models are deterministic, which means that random variations are not considered when calculating the output. A given input will therefore always lead to the same output. When measurement uncertainty affects the input, the uncertainty propagates to the output. Because model based GPA methods have no internal mechanism to handle these effects, the resulting calculated output may be less reliable. This aspect makes model-based GPA methods less suitable for handling measurement uncertainty. Depending on the magnitude of the possible measurement uncertainty, model-based methods may lead to inaccurate GPA results.

A way of differentiating between nominal performance variations and performance deviations resulting from component deterioration is by using empirical GPA methods. Advancements in computer sciences have led to using so-called *artificial intelligence* (AI) methods for GPA. AI methods are defined as methods that 'solve problems in a way which, done by humans, requires intelligence' [20]. Because these methods use experimental or simulated engine data rather than the underlying thermodynamic principles they are referred to as *data-driven* or *empirical* GPA methods in this thesis.

While many empirical GPA methods have been investigated, a detailed analysis of each method is beyond the scope of this thesis. Instead, I will focus on the basic principles of empirical GPA methods by describing the principles of *Genetic Algorithms*, *Neural Networks*, and *Expert Systems*.

Genetic algorithms

Genetic algorithms (GAs), which were introduced by John Holland in the early 1970's [10], are a class of *evolutionary algorithms* that mimic some of the evolutionary processes observed in nature. From a mathematical perspective, GAs are optimization algorithms that use evolutionary principles for finding solutions to numerical problems. Rather than attempting to find a single solution to a set of equations, GAs use a population of possible solutions and use evolutionary mechanisms of selection, cross-over and mutation to reach an optimal solution of a problem.

This approach has some distinctive features that make it suitable for GPA applications [77]: no derivatives are necessary during iteration, constraints are handled effectively by means of penalty functions, and probabilistic methods are used in the process of calculating new populations.

In the field of gas turbine diagnostics GAs have been analyzed in various research projects [56, 77]. These algorithms performed well in the estimation of engine faults, even in the presence of sensor noise and bias [42]. For practical applications there are some drawbacks of this approach. Although multiple fault isolation is possible, fault prediction accuracy decreases with increasing degrees of freedom or fault components [77]. Repeated fitness evaluations for complex problems, such as gas turbine diagnostics, is often a time consuming and forms the limiting aspect of the application of GAs.

Artificial Neural Networks

Inspired by the biological central nervous system, an *Artificial Neural Network* (ANN) is a pattern classification algorithm. A trained ANN will produce a certain output pattern when presented with an input pattern. This method is generally implemented in parallel which makes it capable of high processing speeds, an ideal characteristic for practical GPA applications. Two of the most significant properties of ANNs are their ability to learn and generalize[51]. Programming all possible patterns of a set of sensors would however require an impractical amount of time. Instead, an ANN is given a small number of input patterns for which the outputs are known. These patterns are used to train the network to provide the correct response. When operational, ANNs have–to a certain extent–the ability to interpret characteristics of similar but unknown input patterns and provide the correct estimated output. This property is called generalization. This approach is far more efficient that programming each pattern a priori. Ideally, an ANN provides a correct output even when the input is not explicitly taught. Several different types of ANNs have been successfully used for gas turbine diagnostics [38, 42, 77].

However, these algorithms have some drawbacks when used for GPA. The main drawback of ANNs used for GPA is the complicated network structure that is necessary to solve complex, real-world problems [77]. Another important drawback is the time required for training ANNs; they are *slow learners*. Pattern classification methods can only recognize known patterns; a trained ANN is optimized for the training data set that was used. Although gas turbines are manufactured with tight tolerances, the large number of interacting components means that despite these tight tolerances there are noticeable performance differences among healthy engines [67]. Engine-to-engine differences can introduce variations that require additional training data and time. Obtaining data for the training phase of an ANN is also a challenge.

Expert systems

Another empirical approach for relating measured performance data to component condition deviations is by using *expert systems* (ESs) [12, 14, 65]. The ES concept was developed as an attempt to capture and store expert knowledge and imitate the decision-making process of a human expert [23].

At the core of an ES are a *knowledge base* and an *inference engine*. The knowledge base contains the expert knowledge in a practical format. The inference engine is the computer program that tries solve a problem by interrogating the knowledge base. Because expert knowledge may not always be captured in precise terms, probabilistic and fuzzy logic methods have received considerable attention. For example, different combinations of deteriorated gas path components and levels of deterioration may lead to the similar deteriorated performance.

The main benefit of using ESs for gas path diagnostics is the additional support for interpreting diagnostic data from multiple diagnostic tools simultaneously. This could increase the effectiveness of of specific diagnostic systems considerably. While a great feature of ESs is their ability of being updated continuously by adding new rules or cases to the knowledge base, it is at the same time also a downside. Updates to the knowledge base change the system completely, thereby potentially changing its response to known problems. This implies that each change to an ES requires validation of the complete system. In addition, like other empirical GPA methods ESs rely on large volumes of field data for correct configuration. To develop robust ES system for gas path diagnostics a large number of examples of deteriorated engines are necessary; these are not available.

2.4 Requirements for a GPA tool from a gas turbine MRO perspective

The differences between model-based and empirical GPA methods have been extensively documented in scientific articles. A few comprehensive review articles [38, 42] compared GPA methods in general. They discussed their relative strengths and weaknesses by comparing characteristics such as model complexity, computation speed and the ability to deal with measurement uncertainty. Others focused more on specific methods such as comparing the accuracy of linear and non-linear model-based GPA methods [26], or highlighted the benefits of one particular method in relation to others such as the development of a genetic algorithm optimization method for GPA [77].

Benchmarking GPA methods is mostly done relative to other methods. Because operational turbofan performance data are hard to obtain, most studies on this topic are based on scarcely available real engine data or on simulated data. In fact, many published GPA methods are applied to different engine platforms, with different levels of complexity, addressing different problems, and using different parameters for evaluating performance [58]. This makes an objective comparison of available GPA methods difficult. To help address these inconsistencies, a recent benchmarking study was performed by the NASA Glenn Research Center [58]. However, this study too was based on simulated data.

Other research [24, 66] addressed GPA developments from the broader engine health management (EHM) perspective. Apart from focusing solely on gas path diagnostics, their review also considered other methods used for engine diagnostics. Although they recognized that a good overall EHM solution requires advancements in system architecture, EHM functionalities, and diagnostic algorithms, they noted that the developments in this field were mostly focused on the latter two functional areas.

The criteria used for selecting a GPA tool for the gas turbine maintenance, repair, and overhaul (MRO) industry may be different than for selecting a tool for

From a maintenance, repair, and overhaul (MRO) perspective additional characteristics may be necessary. Indeed, calculation time is an important characteristic of a GPA tool regardless of its application. If GPA is used to analyze data from the post-overhaul performance acceptance tests and an MRO shop annually maintains about 300 engines, one minute per analysis should results in approximately 5 hours of calculation time per year. That should not be a problem. However, if GPA is used for analyzing on-wing measured performance data the time requirements change. A fleet of 100 engines of long-haul aircraft that perform approximately 2.5 flights a day[1] each of which generate

[1]assuming 8-hour flights and 90-minute turn around time

two snapshots per flight, one during take-off and one during cruise, generates approximately 15000 performance snapshots each month. Assuming 1 minute per data set, results in 250 hours calculating time. Conversely, analyzing all 15000 snapshots in 5 hours each month, implies 1.2 seconds per snapshot. While some GPA methods such as linear, non-linear, and neural networks are very fast, genetic algorithms require considerable more time to obtain a solution.

Another important characteristic that is frequently used for comparing GPA methods is accuracy. False alarms and undetected faults resulting from incorrect diagnoses may have financial consequences for an MRO shop. Once poor component condition is correctly identified, it will be partially or entirely disassembled. Each part is subsequently cleaned, inspected for deviations and finally repaired if necessary. Part repair is determined according to the engine repair manual and is not affected by findings from performance diagnostics. Therefore, from an MRO perspective, correctly identifying faulty components is more important than accurately estimating the level of condition deviation. Particularly because GPA results are calculated relative to baseline engine performance.

A typical MRO shop has turbofan overhaul capabilities for multiple engines types from several manufacturers. Turbofan OEMs do offer advanced condition monitoring and diagnostic software specifically designed for their engines to the engine operators and MRO shops. However, this requires sharing operational data. From both the engine operator and MRO shop perspective, this may lead to unwanted insight into company operations. Additionally, the tool may not allow detailed insight in the calculation process leading to diagnoses, and it is available only for engines from that particular manufacturer. For many MROs this would require multiple gas path diagnostic systems, each with its own capabilities, limitations, and associated expenses. Therefore, a single generic GPA tool would be a practical solution.

For MRO shops that develop an in-house gas path diagnostic tool additional aspects are worth considering. For instance, turbofan engines are extremely durable. Because of strict safety requirements imposed by aviation authorities, any fault leading to unexpected failure receives individual root cause analysis. Problems are systematically solved for existing engines and the knowledge is used in the design process of new engines. As a result, the time on-wing of turbofan engines has increased continuously. Modern turbofan engines may remain installed on-wing in excess of 30,000 hours, which amounts to several years without overhaul.

The consequence of those developments is that only a fraction of the installed engines undergo complete overhaul for any given period; a fraction that is shared among competing MRO shops. This fact is highlighted by figure 2.5, which shows the engine MRO shops in western Europe that overhaul the same engines as AFI/KLM Engineering & Maintenance. Because each engine type

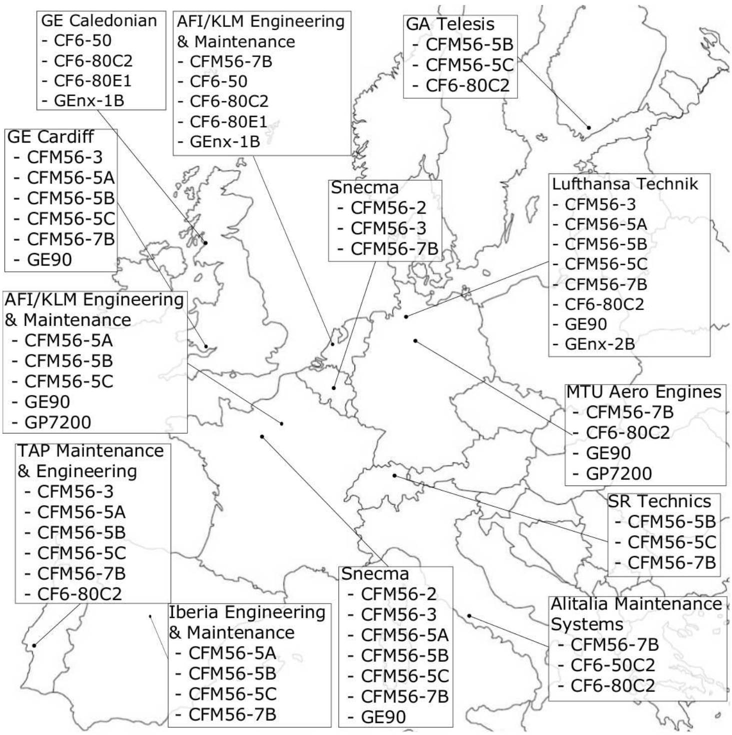


Figure 2.5: *An overview of competing MRO shops in western Europe that overhaul the same engine types as those overhauled by AFI/KLM Engineering & Maintenance. Sources: respective MRO shop websites.*

needs a dedicated GPA tool as well as sufficient data for creating and validating a GPA tool, the number of engines being maintained affects the choice of GPA method that is used for engine diagnostics.

In a similar way in which information fusion may result in improved diagnoses for EHM applications, combining gas path diagnostic data with work scope information may provide additional value for the MRO industry. Correlating maintenance actions to component level condition provides feed back about the effectiveness and quality trends of the maintenance process. Because maintenance-related information may differ among MROs, and because the number of measured parameters may vary among engine types, a flexible information system is key for such applications.

2.5 GSP adaptive modeling methodology

The GPA results described in this thesis were obtained using the Adaptive Modeling (AM) component of the Gas turbine Simulation Program (GSP). GSP is a component-based performance simulation tool capable of modeling virtually any gas turbine configuration [72]. The generic AM component was developed at Delft University of Technology and has been implemented in the component based simulation environment of GSP [73, 74]. This AM component can be embedded in any GSP model thereby converting it into a non-linear diagnostic model for gas path analysis purposes without the need for additional coding.

During an AM calculation the performance model is adapted until it matches measured engine performance[74]. Because the performance model is adapted by adapting its gas path component characteristics, the required adaptation is a measure of the component condition deviations between a measured and a reference performance data set. Section 2.3.1 described how map modifiers are used for matching a performance model to measured data. Figure 2.6 shows the effect of the corrected mass flow map modifier on the constant speed lines of a compressor map. Similarly, map modifiers are used for adapting the isentropic efficiency during the AM calculation.

One step of the adaptive modeling calculation is model calibration. This step is necessary for removing residual model-reference measurement deviations. Calibration factors scale model performance parameters to match reference engine performance. These factors remain constant during AM calculations.

For the AM calculation GSP combines the numerical modeling methods described in section 2.2 with the AM concept described in section 2.3.1. It uses an integral approach, where the performance model equations are solved simultaneously with the additional non-linear differential equations necessary for the adaptive model. This way the effects of adapted component characteristics on

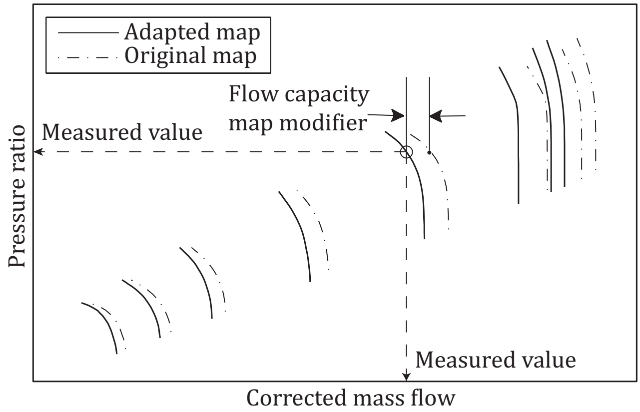


Figure 2.6: *This figure shows an example of a compressor map adapted by a flow capacity map modifier. Component characteristics are adapted such that a steady state operating point is obtained that matches measured engine performance. For the compressor map the measured values used for adaptation are pressure ratio, corrected mass flow and corrected compressor rotational speed.*

model performance are taken into account. The resulting set of equations take the form of equation 2.12 [74]. In this equation, f_1 to f_n in the upper-half are the error equations that represent the reference engine, and f_{m1} to f_{mm} in the lower-half represent the additional equations necessary for the AM calculations. s_1 to s_n are the unknown model states that need to be solved, and s_{c1} to s_{cm} are the scalars that represent the condition parameters that need to be solved. ϵ_1 to ϵ_n are the relative equation tolerances for which the model states need to be solved to satisfy the conservation laws and are close to zero, and ϵ_{m1} to ϵ_{mm} represent measurement tolerances for solving the additional AM equations and states. These measurement tolerances are specified separately in the AM component. GSP uses a Newton-Raphson-based method for solving the set of non-linear differential equations.

$$\left[\begin{array}{ccc|ccc} f_1(s_1)+ & \cdots & f_1(s_n)+ & f_1(s_{c1})+ & \cdots & f_1(s_{cm}) \\ \vdots & & \vdots & \vdots & & \vdots \\ f_n(s_1)+ & \cdots & f_n(s_n)+ & f_n(s_{c1})+ & \cdots & f_n(s_{cm}) \\ \hline f_{m1}(s_1)+ & \cdots & f_{m1}(s_n)+ & f_{m1}(s_{c1})+ & \cdots & f_{m1}(s_{cm}) \\ \vdots & & \vdots & \vdots & & \vdots \\ f_{mm}(s_1)+ & \cdots & f_{mm}(s_n)+ & f_{mm}(s_{c1})+ & \cdots & f_{mm}(s_{cm}) \end{array}\right] \leq \begin{pmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \\ \epsilon_{m1} \\ \vdots \\ \epsilon_{mm} \end{pmatrix} \tag{2.12}$$

The component-based modeling capability of GSP and the generic AM component that can convert any GSP model into a diagnostics model together form a flexible model-based GPA tool. In contrast to GPA tools developed by the engine manufacturers, it is not restricted to engines from a single manufacturer. Most performance data necessary for creating a performance model for GPA applications is available to the aero-engine MRO shops. This includes the design point performance data such as component efficiency, mass flows, and fan bypass ratio. Occasionally off-design performance data may also available for specific engine power settings. However, off-design component performance data are usually not available. Therefore, specific engine data such as component maps and variable geometry control schedules are approximated by data available from other engines, or by reverse engineering using measured off-design performance data.

2.6 Conclusion

- GPA is an effective method for assessing engine condition on component level without the need for engine removal or disassembly. This makes it a good addition to the existing gas turbine diagnostic methods that are used for on-condition maintenance strategy.

- Gas turbine performance models are important for developing any GPA method. Whether they are used directly in model-based GPA methods or for developing and training empirical GPA methods, improving performance model accuracy will have a direct impact on the accuracy of the GPA method.

- In theory empirical GPA methods have characteristics that are beneficial to the reliability of the results. They are better equipped to handle measurement uncertainty effects compared to model-based methods, some methods are capable of solving large complex problems in very short time, and they are capable of finding the optimal solution. However, a large number of data sets of faulty engines are necessary for creating a robust diagnostic tool. Without sufficient data empirical GPA methods cannot reliably detect engine faults. Because data sets of engines with particular faults are scarce, developing robust empirical GPA methods is mostly limited to gas turbine manufacturers.

- Empirical GPA methods such as artificial neural networks and expert systems are abstract and are best approached by end users as a black box. Although for end users the empirical approach removes the need for understanding the complex gas turbine behavior, it makes it very difficult–if not impossible–to verify the GPA results.

- Gas turbine part repair or replacement is dictated only by the engine repair manual. Specialized diagnostic methods are used for determining if a specific part must be replaced or repaired. This is not based on findings from performance diagnostics. Therefore, correct root cause identification with GPA is more important than accurately estimating the degree of component condition deviation. The added value of GPA in the maintenance process is to better estimate the maintenance work scope and limit premature repair of components that still show adequate performance.

- GPA is a mature technology. Despite the advances made in this field, there are some fundamental aspects that were not tackled by the development of additional GPA algorithms: performance measurements will always contain some error, detailed design data of operational engines will remain proprietary, and there will always be a shortage of measured parameters. Therefore, enhancing the added value of this diagnostic technology is likely to occur by making smarter use of available information for improving accuracy as well as integrating GPA into the aero-engine maintenance process.

- Selecting the right GPA tool for integrating into the aero-engine maintenance process depends on more than calculation speed and diagnostic accuracy. While these aspects are important for operational GPA tools, creating a practical GPA tool is the first step to be taken. For aero-engine maintenance applications where the development of a GPA tool and tuning it to specific engine models is done by the MRO shop rather than the engine OEM, reasonably small data sets are necessary for creation and validation. For those applications, generic, model-based methods are better suited for integrating GPA into the maintenance process.

CHAPTER 3

Gas path analysis with GSP

Abstract

Advanced model-based diagnostic techniques enable component condition estimation without the need for engine disassembly and are an essential addition to the on-condition maintenance process. However, several aspects limit systematic use of these techniques in the maintenance process. This chapter presents the experience of using GSP GPA in an aero-engine maintenance process. It focuses on the potential of GPA to enhance the process. GPA capabilities in relation to the needs of the aero-engine maintenance process are analyzed, improved and extended for new application areas. Several case studies are presented including a feasibility study of using on-wing measured performance data instead of test cell performance data, and a study on on-wing exhaust gas temperature margin assessment by means of gas path analysis.

The content of this chapter is based on:

Verbist, M.L., Visser, W.P.J., van Buijtenen, J.P., and Duivis, R., **Model-based gas turbine diagnostics at KLM Engine Services.** International Symposium on Air Breathing Engines 2011. ISABE-2011-1807

Verbist, M.L., Visser, W.P.J., van Buijtenen, J.P., and Duivis, R., **Gas path analysis on KLM in-flight engine data.** ASME Turbo Expo 2011. GT2011-45625

TURBOFAN engines are complex machines that require regular maintenance to ensure safe, reliable and cost-effective operation. Engine diagnostic methods and maintenance strategies are as old as the gas turbine itself and have evolved considerably over time. Gas path analysis (GPA) is a diagnostic method that can isolate and quantify the relative severity of problems that affect engine performance. GPA has several benefits that may enhance preventive and condition-based maintenance strategies that are commonly used for turbofan maintenance. Research on this topic in the late 70's and early 80's have lead to the development of several GPA tools from the gas turbine original equipment manufacturers (OEMs) such as TEMPER [13], developed by General Electric, and COMPASS [53], developed by Rolls Royce. While these methods were a considerable step forward in the field of gas path diagnostics, their accuracy was not always sufficient for maintenance applications. Since then the research in this field has been mainly focused on improving the accuracy of GPA methods.

Even though the benefits of GPA for gas path component diagnostics are widely accepted, few articles describe field experience with GPA in the aero-engine maintenance process. This lack of publications suggest that despite its potential for enhancing the maintenance process GPA is not used systematically in the MRO industry or the experience obtained by MROs is not shared with the gas turbine community. To fill that gap, this chapter presents the experience of using GSP GPA in an aero-engine maintenance process.

The GSP adaptive modeling component that is used for GPA is being used since 2004 for the analysis of several CF6 and CFM56 engine families that are maintained at KLM Engine Services [3, 4, 11, 18, 50, 64, 69]. In addition, the GPA capability of this tool has also been successfully demonstrated for the Rolls-Royce GEM42 turboshaft engine operated by the Royal Dutch Navy [45, 52], the Pratt&Whitney PW120A turboprop engine maintained at Standard Aero [45], and the Honeywell GTCP 131-9B auxiliary power unit maintained at the EPCOR [76]. By analyzing the GPA capabilities in relation to the needs of the aero-engine maintenance process, this study presents new and improved GPA methods and application areas for improving the maintenance process.

3.1 Application to turbofan engines

After overhaul, turbofan engines are subjected to a mandatory performance acceptance test to verify that the required performance levels are achieved without exceeding engine limits. To determine engine performance during these *post-overhaul* acceptance tests, parameters are measured that indicate the energy in- and outflow, the engine's mechanical operation and the state of the working medium at several locations along the engine gas path. These parameters, shown in figure 3.1, are collectively referred to as the *performance parameters*.

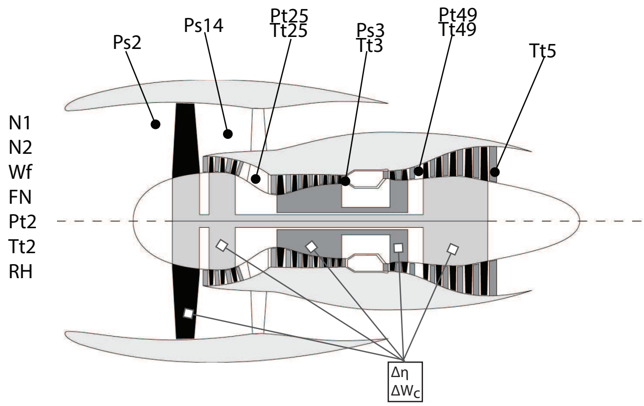


Figure 3.1: *Schematic of a typical turbofan engine including the rough location of the performance parameters observed during a typical post-overhaul acceptance test. The component condition parameters ($\Delta\eta$ and $\Delta\,Wc$) resulting from GPA are also shown.*

Because measured performance parameters are affected by the combined deterioration level of each gas path component as well as changes in atmospheric condition, engine power setting and possible measurement errors, the deviation of any performance parameter by itself is not necessarily an indication of gas path component deterioration. To reveal the hidden information contained in measured performance data additional analysis is required. There are several methods to achieve this.

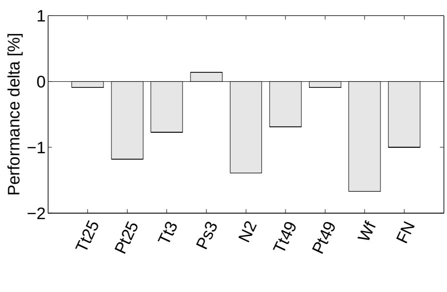
One approach is to correct observed performance parameters for known power setting, atmospheric effects and component losses. This way, important performance parameters are defined such as exhaust gas temperature (EGT), specific fuel consumption (SFC) and corrected engine speed that can be compared to operational limits defined by the engine OEM. This is referred to as performance monitoring or trending. The differences between corrected performance parameters and their limiting values defined by the engine OEM are so-called *performance margins*. When observed over time, these performance margins provide useful information about the change of engine condition and fuel efficiency. Even though this approach provides an effective way of monitoring engine performance and its condition, it cannot be used to determine the root cause when an engine exhibits poor performance.

Another approach is to use GPA for estimating the condition of individual gas path components. This approach enables root cause identification when poor engine performance is observed. Post-overhaul engine performance tests provide accurate and sufficient performance data for detailed GPA. Depending on the available measured performance parameters and engine configuration, component condition parameter deviations ($\Delta\eta$ and ΔWc) can be estimated for some or all gas path components of a gas turbine engine.

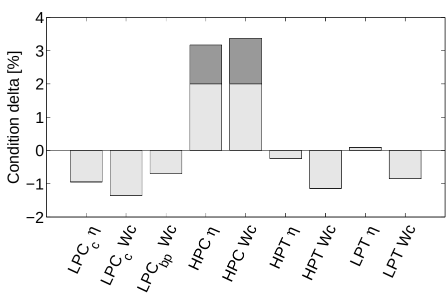
A valuable application of GPA is troubleshooting engines with poor performance. Maintenance work scopes are customized for each engine. While the majority of overhauled engines successfully pass the post-overhaul acceptance test, occasionally engines fail this test. When this occurs it often results in increased maintenance costs and time. Depending on the specific maintenance contract with the engine operator, this may result in significant reduction or complete loss of the profit margin for that particular engine. When poor performance is the reason of failure, the component level condition estimation obtained by means of GPA point at the root cause of the observed performance problem. The repair work scope for the failed engine can then be based on the actual component condition. This minimizes the additional maintenance work and time.

3.1.1 Case study: troubleshooting a rejected engine

The example presented in this section demonstrates how GPA can be used for troubleshooting poor engine performance. A maintenance work scope for a CF6-80C2 engine was agreed with the engine operator that should result in a specified EGT margin. The work scope included a full overhaul of the HPC and HPT, which should restore sufficient engine performance. Despite the work scope however, this engine failed its post-overhaul performance test because of a low EGT margin. The measured performance data of the failed performance tests are shown in table 3.1. The location of performance parameter measurements is illustrated in the turbofan schematic in figure 3.1.



(a) performance deviation chart



(b) condition deviation chart

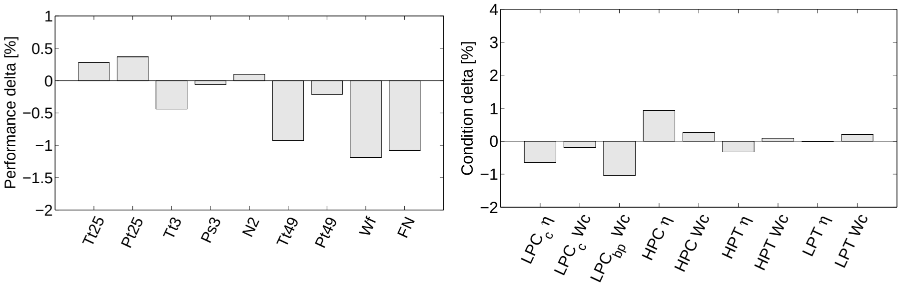
Figure 3.2: *GPA results using performance data of the rejected performance test. While the HPC condition is better than the reference condition, the remaining components show slightly below average condition.*

Table 3.1: *Measured and calculated performance parameters of the rejected and accepted performance test, and reference data used for GPA.*

Parameter	Unit	Failed	Accepted	Reference
FN margin	kN	5.080	5.009	4.626
EGT margin	K	23	31	39
N2 margin	rpm	194	171	60
N1	rpm	3569	3525	3525
N2	rpm	10490	10353	10537
FN	kN	256.16	257.37	255.56
Wf	kg/s	2.72	2.68	2.69
Tt49	K	1139	1102	1123
Tt2	K	293	284	289
Tt25	K	394	384	389
Tt3	K	846	822	838
Tt5	K	-	-	-
Ps13	bar	1.384	1.386	1.420
Pt2	bar	1.002	1.005	1.007
Ps2	bar	0.744	0.746	0.746
Pt25	bar	2.571	2.604	2.593
Ps3	bar	32.432	32.877	32.063
Pt49	bar	7.687	7.775	7.612
Pt2	bar	1.007	1.010	1.011
RH	%	52.66	84.88	78.93

GPA result of with the performance data of the failed acceptance test are shown in figure 3.2. The reference data used for GPA are shown in the rightmost column of table 3.1. Based on the initial work scope and inspection after the failed performance test, a restoration work scope was planned. GPA results indicated an increased booster mass flow capacity relative to the reference engine. Based on these GPA results and to avoid additional rework on the high pressure compressor, it was decided to restore booster clearances to gain some extra EGT margin. The booster is more readily accessible compared to the high pressure compressor. After additional repair the engine condition improved, indicated by the EGT margin increase of 7K shown in table 3.1, and the engine successfully passed the acceptance test.

Figure 3.3 present the results of the GPA run after additional repairs. It shows the improved condition relative to the rejected engine condition. The performance deltas shown by the bar chart in figure 3.3(a) indicate, for instance, that engine had reduced EGT (Tt49) and fuel flow (Wf)for the same corrected fan speed after additional repair. The condition deltas shown in figure 3.3(b)



(a) performance deviation chart (b) condition deviation chart

Figure 3.3: *GPA results after additional repairs. The bar charts show the performance and condition condition deltas of the repaired engine. These deltas are relative to engine performance before the additional repairs.*

suggest that the most significant component condition changes were realized in the LPC bypass flow capacity (LPC Wc_{bp}) and the HPC efficiency (HPC η). Even though the HPC did not receive additional repair work, its efficiency did improve. This improvement is most likely caused by aero-thermodynamic component interaction where the outflow conditions of the LPC core better matched the HPC for those operating conditions.

This case study is an example of a GPA application for aero-engine maintenance process. Although in this particular case the engine condition only showed small improvements after additional maintenance resulting in a 7K increase of the EGT margin, it demonstrates how GPA results can help planning maintenance work scopes. Such information is most valuable for the maintenance process before overhaul.

3.2 GPA potential for aero-engine maintenance and condition monitoring

As mentioned in the previous section, typical GPA applications include post-overhaul component condition monitoring and troubleshooting engines with poor performance. For such applications it could suffice to use GPA on a case-by-case basis. However, embedding GPA in the maintenance process and systematically using it for every measured performance data set could offer substantial benefits for the aero-engine maintenance process in terms of cost reduction and enhanced maintenance effectiveness.

Figure 3.4 shows a simplified representation of the maintenance process that a turbofan engine repeats several times during its operational lifetime. While

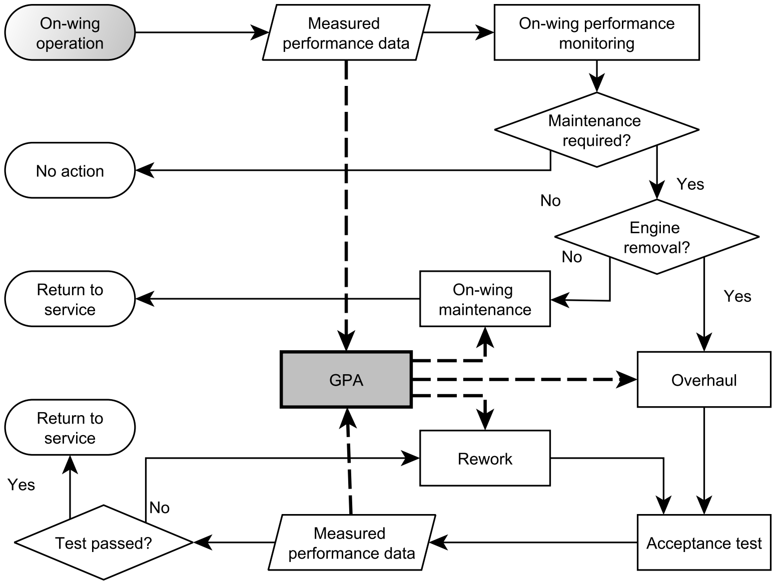


Figure 3.4: *GPA embedded in a simplified representation of the turbofan maintenance process. The necessary performance data would be obtained from measurement during on-wing operation as well as during performance tests. Knowledge of the estimated component condition obtained by means of GPA could be beneficial for on-wing maintenance, overhaul and for the additional rework when a engine fails its post-overhaul performance test.*

installed on-wing, engine performance monitoring is used to observe the condition deterioration process over time and to assist the on-wing maintenance process. When engine removal is required either due to poor performance or triggered by life-limited parts, available performance trends can be used to determine the necessary maintenance work scope. While some engine operators systematically use a dedicated performance test prior to overhaul to help estimate the necessary work scope, this is not done by all operators. When GPA would only be used on a case-by-case basis for troubleshooting engines with poor performance after overhaul, the maintenance process only receives useful information from GPA when an engine fails the post-overhaul performance test or when an inbound test run is performed, neither of which occur regularly.

The aero-engine maintenance process could benefit from the additional information if GPA were embedded in the maintenance process and used systematically. By using performance data measured during on-wing operation as well as from engine tests for GPA, detailed component condition information would be available at all times during its operational life. In addition to providing more detail of the condition deterioration process, this information would be useful for planning work scopes by knowing the actual engine condition. Because component condition information would be available before and after the maintenance work, the effectiveness of the maintenance would also become measurable. This knowledge, in turn, could be used optimize maintenance effectiveness and possible predict the impact of a work scope. That way, engine repair shops could provide their customers with predictions about the costs related to performance restorations.

3.2.1 Adapted-model performance analysis

One GPA application that has been successfully used in the aero-engine maintenance process is *adapted-model performance analysis*. It is a method whereby the performance of an engine is compared to the performance of an engine model that has been tuned to more accurately represent that engine than the baseline performance model. The baseline model is adapted by using the component condition parameter deviations obtained by means of GPA. Adapted-model performance analysis can be used to verify the performance and condition of an engine with a known initial condition over a period during which its condition should remain unchanged but where performance measurements suggest otherwise. When too few measured performance parameters are available for GPA, adapted-model performance analysis can offer more insight than performance parameter trending. This method has been proven useful for analysis of engines with abnormal on-wing performance that had been recently overhauled but had too few on-wing measured performance parameters for detailed GPA.

Normally there are small performance differences between different engines. This is the result of small variations in the manufacturing, deterioration and maintenance processes. Because not all gas path modules are overhauled during a shop visit, engine-to-engine performance variation increases as they age. During overhaul gas path components may undergo different maintenance work scopes depending on their condition. This could result, for instance, in engines that have overhauled HPC and HPT modules but largely untouched fan, booster, and LPT modules. Because of such differences, engine performance changes during its operational life and simulation models that have been developed for new engine performance may not accurately represent every engine. By adapting a baseline performance model to the condition of a particular (overhauled) engine, existing performance differences are minimized. This allows more accurate analysis of small performance deviations.

3.2.2 Case study: On-wing EGT margin validation

An example case for which adapted-model performance analysis was used at KLM ES was the analysis of EGT margin abnormalities of an CFM56-7B engine. The CFM56-7B is a relatively small two-shaft turbofan engine used for the Boeing 737 aircraft series. In general the hot day EGT margin, i.e., the EGT margin corrected for hot day operating conditions, is a good indicator of overall engine condition from a performance perspective. As the condition of an engine deteriorates over time, its hot day EGT margin reduces. Consequently, the hot day EGT margin is an important parameter for engine operators, which often demand a minimal EGT margin after engine overhaul. A relatively low EGT margin is an indication of poor engine condition and suggest a shorter time between consecutive overhauls from a performance perspective.

This case study describes a situation in which there were several overhauled CFM56-7B engines for which the on-wing hot day EGT margin deviated significantly from hot day EGT margin that was established during the post-overhaul acceptance test. Also, for some engines severe scatter of the hot day EGT margin was observed during on-wing operation. Figure 3.5 shows a schematic of the CFM56-7B engine and the measured performance parameters. The engines were overhauled at KLM ES and successfully passed the post-overhaul acceptance test. The EGT margins determined during the acceptance test were as expected for an overhauled engine. Upon closer inspection of KLM's own CFM56-7B fleet, no maintenance-related cause was identified that could explain this unwanted behavior [18].

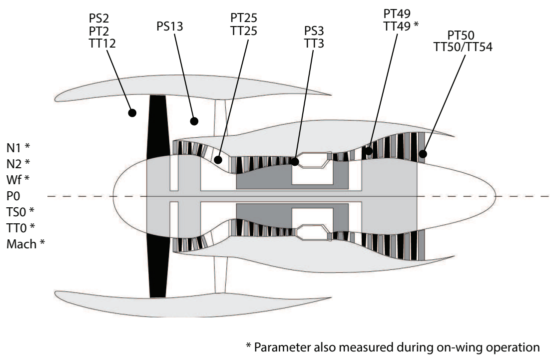


Figure 3.5: *CFM56-7B performance parameters measured during test cell and on-wing operation.*

Even though GPA is an excellent method to investigate this discrepancy, the CFM56-7B engines for which performance data were available for analysis were equipped with a sensor package that provided too few on-wing measured performance parameters for detailed GPA. Instead, adapted-model performance analysis was used.

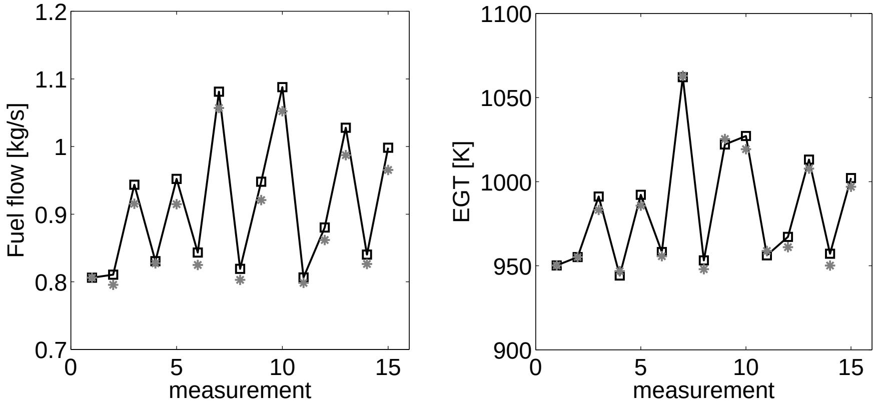
By using this method the performance parameters that were measured on-wing could be compared to simulated engine performance parameters that were obtained for identical operating conditions. This approach works as follows. For every engine analyzed, the post-overhaul performance data were used to adapt the GSP engine model. The adapted model therefore represented an engine with specific and constant post-overhaul condition. Next, the adapted model was then used for simulating engine performance at engine power setting (N1) and ambient conditions (TT0, PT0) that were measured during the 15 first on-wing take-offs. During the initial period on-wing after overhaul, gas turbines show a relatively rapid loss of EGT margin due to seal run-in. Because this period of relatively rapid EGT margin loss can take up to 1000 engine flight cycles [7], however, it was assumed that no significant changes should occur during the first 15 take-offs.

The performance parameters used for comparison were core engine speed (N2), fuel flow (W_f), and EGT (Tt_{49}). The results of the performance simulations are shown in figure 3.6. The close match of the measured and simulated fuel flow and EGT, shown in figure 3.6(a) and figure 3.6(b) respectively, indicate that the on-wing measured engine performance thermodynamically corresponds to the simulated engine with a constant condition. Any small deviations that remained may be because of model inaccuracies and additional effects not measured such as customer bleed and power off-take.

Moreover, these deviations are an order of magnitude smaller than the EGT margin variation. A gas turbine with a constant condition should have a constant corrected EGT margin. Instead, the hot day EGT margin that was observed during the first 15 take-offs after engine overhaul varied significantly. This is shown in figure 3.7(b). The hot day EGT margin values of figure 3.7 were obtained by the engine condition monitoring software from the engine OEM. Similar results were obtained for several engines.

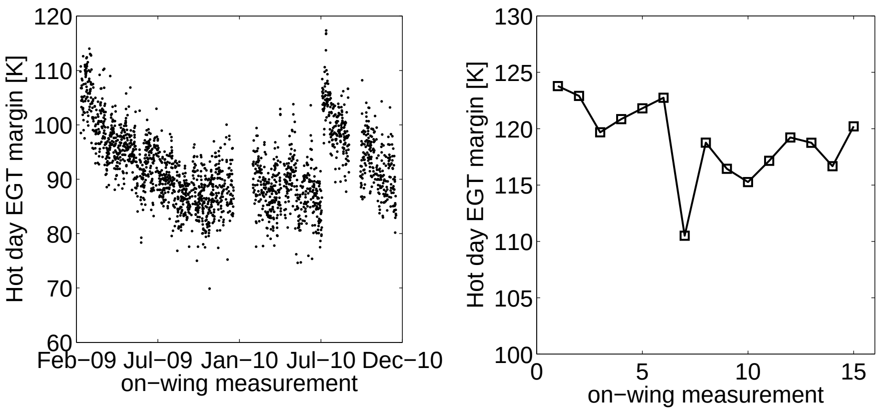
Power setting, operating conditions, customer bleeds, accessory drive loads, and other installation losses affect the EGT. Consequently, the calculated EGT margin should be corrected for those effects. If performed correctly, variations of the hot day EGT margin should be only because of component deterioration and thereby reflect overall engine condition. Based on the results of this analysis it was concluded that the cause of the hot day corrected EGT margin deviation and scatter were not the result of engine deterioration or measurement error. More importantly, these results suggest that the hot day EGT margin calculations are inaccurate or based on false input data.

This case study shows how GPA still enables verification of on-wing performance and condition when too few measured performance data are available for detailed GPA. This application improves the information flows between the off-



(a) Fuel flow trend (b) Observed EGT trend

Figure 3.6: *Comparing results of adapted-model performance analysis and on-wing measured performance data for fuel flow (figure 3.6(a)) and exhaust gas temperature (figure 3.6(b)).*



(a) (b)

Figure 3.7: *Hot day EGT margins of an engine with severe scatter 3.7(a) and the EGT margin observed during the 15 first take-offs of engine used for the study 3.7(b).*

wing maintenance process and on-wing performance. Not only does it provide additional insight of on-wing engine behavior, it also provides a cost-effective alternative to performance test runs.

3.2.3 On-wing component condition monitoring

Another practical application of GPA in the aero-engine maintenance process is *component condition monitoring* using on-wing measured performance data. In section 3.1, several examples were discussed regarding the use of gas path analysis at KLM ES. Those GPA applications all used performance data that are measured after engine overhaul. Although useful, GPA results can become much more effective for the maintenance process if they were available before maintenance. Performance tests prior to engine maintenance provide such an opportunity. Unfortunately, the additional costs for these *in-bound* performance tests ensure minimal use of this opportunity. Another source of engine performance data is performance data that are measured during on-wing operation. If on-wing measured performance data could be used for GPA, this would eliminate the need for performance tests prior to engine maintenance. Moreover, analyzing on-wing measured performance data with GPA tools would provide a much more detailed view of the engine condition and deterioration trends.

Conventional Engine Condition Monitoring (ECM) systems and Engine Health Management (EHM) systems record measured performance data during engine operation and alert the operators when a parameter shift or exceedance occurs. Without additional analysis of the observed data, such systems cannot identify the root cause of a parameter shift or exceedance. Using GPA for additional analysis of the on-wing measured performance data would allow root cause analysis of observed parameter shifts and exceedances. It would then become possible to determine whether a parameter shift or exceedance is caused by sudden deterioration of a single component, the combined effect of multiple component deterioration or the result of sensor error.

Hypothetically, when used in combination with airline operational data, such techniques could have far reaching benefits for airline operations. If component condition deterioration could be correlated to flight routes, there would be an opportunity to optimize aircraft deployment to maximize engine on-wing time. Additionally, on-wing component condition monitoring would enable engine health prognostics. Such capability could be very beneficial for maintenance work scope planning.

3.2.4 Fewer on-wing measured performance parameters

An important condition for successfully using on-wing measured performance data for GPA is the availability of sufficient measured performance parameters. During performance tests in a test cell, gas turbines have more sensors installed for performance measurements than during on-wing operation. To certify engines for on-wing operation after overhaul, detailed engine performance assessments are required. Therefore, engines are equipped with the necessary sensors to determine their performance to the required level of detail during the post-overhaul acceptance test. While a minimum set of sensors is required for control purposes during on-wing operation, installing additional sensors depends on the engine operator. Adding extra sensors is a consideration between the added cost of additional sensors and their maintenance, and the value of the additional performance data that can be measured during on-wing operation. Because extra costs are more tangible than the perceived value of extra engine performance data, often only the sensors necessary for control purposes are installed during on-wing operation. In addition, some performance parameters cannot be measured during on-wing operation. As a result, the on-wing measured performance parameters are often insufficient for detailed GPA.

One performance parameter that cannot be directly measured on-wing is engine thrust. Engine thrust represents the thermodynamic state of the core and bypass nozzles. During post-overhaul acceptance tests in a test cell, load cells are used to accurately measure engine thrust. Because thrust measurements are not possible on-wing, an alternative parameter is required to represent the thermodynamic state of the nozzles. For high bypass turbofan engines a large fraction of the thrust, in the order of 85% of the total thrust, is generated by the bypass flow. The pressure ratio over the fan bypass nozzle governs the thrust generated by the bypass flow. Therefore, the fan bypass outlet pressure represents the state of the bypass nozzle, which makes this performance parameter a good alternative to the thrust parameter.

A comparative analysis has been performed to verify the use of fan outlet pressure as an alternative parameter to represent the thermodynamic state of the exhaust nozzles. Of the performance parameters measured during the performance acceptance test of the CF6-80 engine in the KLM Engine Services test cell, 14 parameters can be used for GPA purposes including engine thrust and fan outlet pressure.

Table 3.2 provides the list of the available measured performance parameters. Tt0, Pt0 and RH define the atmospheric condition, and N1 defines the engine power setting. The 10 remaining parameters represent the thermodynamic state of the engine. However, using the thrust and the fan bypass outlet pressure simultaneously in the AM calculations results in an ill-conditioned system. Therefore, from the available set of performance parameters 9 component condition parameters can be determined simultaneously. For the comparative analysis, the performance test data from recently overhauled engines was used. The AM calculations were done twice; first with the direct thrust measurement and subsequently with the fan bypass outlet pressure.

Table 3.2: *Measured performance parameters that were available for GPA.*

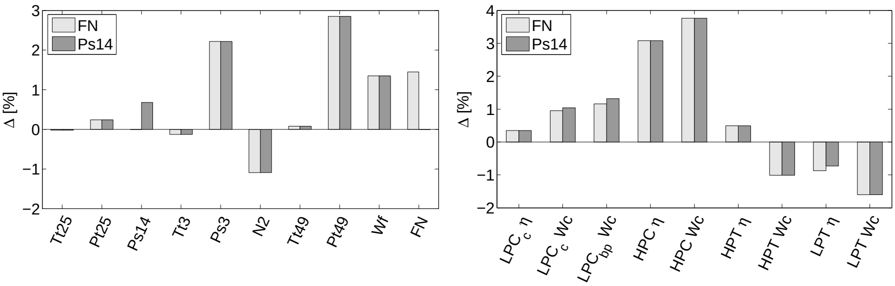
Parameter	Description
Tt0	Ambient temperature
Pt0	Ambient pressure
RH*	Relative humidity
N1	Fan shaft speed
Ps14	Fan bypass static outlet pressure
Tt25	Booster outlet total temperature
Pt25	Booster outlet total pressure
Tt3	HPC outlet total temperature
Ps3	HPC outlet static pressure
N2	Core shaft speed
Tt49	HPT outlet total temperature
Pt49	HPT outlet total pressure
Wf	Fuel mass flow
FN*	Engine thrust

* parameter not measured during on-wing operation.

The results of this analysis are presented in figure 3.8. The top bar chart shows the performance parameter variations necessary to adapt the engine model to measured performance of a particular engine for both simulation runs. This chart illustrates that for the first AM calculation, measured thrust (FN) was used, whereas for the second AM calculation the fan outlet pressure (Ps14) was used. The bottom two charts illustrate component condition deviations relative to the reference engine condition. The results indicate only a minimal differences in the diagnostic outcome. Similar results were obtained for other engines. These results validate the use of fan outlet pressure for GPA of on-wing data as a suitable alternative for thrust measurements.

3.2.5 Reference engine condition

Model-based diagnostic tools compare measured engine performance to reference engine performance, both operating at matching operating conditions. Because the condition of a reference engine has a direct effect on GPA results, knowledge about that condition is important for validating GPA results. To understand this concept consider the following thought experiment. A performance data set of an engine requiring maintenance is analyzed two times by means of GPA. The first analysis is done by using a reference data set of an engine with best possible performance, i.e., the highest possible EGT margin for that engine type. The second analysis is done by using a reference



(a) Performance deviations (b) Condition deviations

Figure 3.8: *GPA results showing the effects of using fan outlet pressure (Ps14) as a proxy for the direct thrust measurements (FN) that are not available during on-wing operation.*

data set of an engine with poor performance, i.e., zero EGT magin. The GPA results of those two cases will be wildly different. The results obtained with new-engine performance as reference will likely exhibit significant *negative* condition deviations on most, if not all, gas path components. This would suggest that all gas path components should be overhauled and provides little information for estimating a realistic maintenance work scope. Maximum performance restoration will only be achieved when all engine components are overhauled. But due to financial considerations this usually does not occur in practice. In contrast, the GPA results obtained with a zero-EGT-margin reference engine will likely show significant *positive* condition deviations. Those results could suggest that most, if not all, gas path components are in good condition. That too would provide little information for estimating a maintenance work scope. Thus, using a *representative* reference engine is essential when GPA result are used for estimating maintenance work scope. The rule of thumb used in the MRO industry is that engine overhaul may result in up to 80% of new engine performance.

The GSP performance models and reference engines used for GPA have been developed and selected by KLM. The selected reference engines are engines of a particular model and type with average performance after a gas path overhaul or performance restoration at the MRO facility. Insight into performance model accuracy and reference engine condition enables fair judging of the results and provides a more realistic view on the possible component condition restoration.

3.2.6 Measurement uncertainty

As with other GPA methods, the results of model-based GPA are affected by measurement uncertainty. The uncertainty of a measured quantity arises due to random and systematic measurement errors and reflect incomplete knowledge of the quantity being measured. In the case of GPA measurement uncertainty perturbs the true values of measured performance parameters and therefore any subsequent analysis based on those parameters [38, 42].

To better understand the effects of measurement uncertainty on GPA results, the effects of random sensor noise were studied with GSP. For this analysis, component deterioration was simulated for the high pressure compressor and high pressure turbine of a CF6-80C2 engine. The simulated deterioration levels are shown in the boldface printed column in table 3.3. To simulate the effects of sensor noise, random variations were added to simulated performance parameters, with the exception of the shaft RPM. Because shaft rotational speed measurements are generally accurate, noise effects on these parameters are neglected in this analysis. Four levels of sensor noise are used, namely: ±0.5%, ±1%, ±2% and ±4%. For each level of simulated sensor noise, 20 sets of perturbed performance parameters were generated by using the MATLAB® *randn* function. GSP's adaptive modeling component was used to analyze both the unperturbed and noise affected performance data.

The results of this study are presented in box-and-whisker plots in figure 3.9. The results show that relatively small performance parameter variations that may be caused by sensor noise can have significant effects on the diagnostic outcome. For example, performance parameter perturbations within the ±1% range lead to condition parameter deviations of several percent. This effect appears to increase for increased levels of simulated sensor noise. The results also show that effects of sensor noise are not equal for all condition parameters. Some component condition parameters shown much larger deviations for a specific noise level in comparison to other condition parameters. In addition, the condition deviation extrema increase for increasing levels of sensor noise. Based on these characteristics, sensor noise appears to be disastrous for GPA. Especially when few data points are available for GPA.

However, for each flight at least one performance data set is recorded. Furthermore, gas path component deterioration is in the majority of cases a slow and steady process. This means that over a period of several flights the condition of gas path components usually do not change noticeably. Therefore, the availability of many on-wing performance data points recorded consecutively permits averaging of the results affected by sensor noise. In this study mean component condition deviations were determined by using 20 data points per parameter for each level of simulated sensor noise. These results are presented in table 3.3. They show that averaging the results affected by random error leads to reasonable approximations of the actual component condition deviation. For all levels of simulated sensor noise, the GPA results still captured those components with poor condition, albeit less accurate for increasing levels of sensor noise. Thus GPA results affected by random sensor error can be averaged to approximate the true component condition provided that the performance data are obtained in a short period during which the condition of the engine should not change noticeably.

Table 3.3: *GPA results of simulated sensor noise analysis. The column printed in boldface shows the simulated engine condition. The remaining columns show the mean values of the GPA results for the different levels of simulated random sensor noise.*

Condition Parameter	Simulated Deterioration	0.0%	0.5%	1.0%	2.0%	4.0%
$LPC_c\Delta\eta$	**0.0**	0.0	-0.1	-0.8	0.8	2.2
$LPC_c\Delta Wc$	**0.0**	0.0	-0.1	0.0	0.0	-0.3
$LPC_{bp}\Delta\eta$	**0.0**	-	-	-	-	-
$LPC_{bp}\Delta Wc$	**0.0**	0.0	-0.1	-0.2	-0.2	-1.2
$HPC\Delta\eta$	**-2.0**	-2.3	-2.4	-1.8	-1.4	-0.9
$HPC\Delta Wc$	**2.0**	2.1	2.1	2.4	2.5	1.3
$HPT\Delta\eta$	**-3.0**	-3.0	-2.9	-3.3	-2.6	-3.7
$HPT\Delta Wc$	**-1.0**	-0.7	-0.6	-0.7	-0.8	-1.0
$LPT\Delta\eta$	**0.0**	-0.1	-0.1	0.0	-0.6	-0.1
$LPT\Delta Wc$	**0.0**	0.3	0.4	0.7	-0.2	0.3

3.2.7 Case study: GPA with on-wing measured performance data

GPA with on-wing measured performance data was attempted for three General Electric CF6-80C2 engines installed on the same aircraft of the KLM fleet. Because the GPA model including the component maps are tuned to test cell standard take-off conditions, take-off performance snapshots were used to assess the application of on-wing GPA. For each engine, 25 consecutive on-wing take-off snapshots were available. These take-off snapshots were recorded 50 seconds after commencing take-off mode in the Flight Management System (FMS).

The engines used for this study were equipped with an extended sensor package that measured 12 different parameters. In addition to 3 performance parameters required to observe atmospheric conditions and power setting, 9 additional performance parameters were available for GPA. Table 3.2 provides a list of the on-wing measured performance parameters. With these 9 performance parameters, 9 component condition parameters could be determined by means of GPA. For each engine, performance data from the last test cell acceptance test was used as reference for model calibration.

Figure 3.10 shows the GPA results for the three CF6-80C2 engines. The scatter observed in these graphs was likely caused by the combined effects of measurement uncertainty and model error. When these results are compared

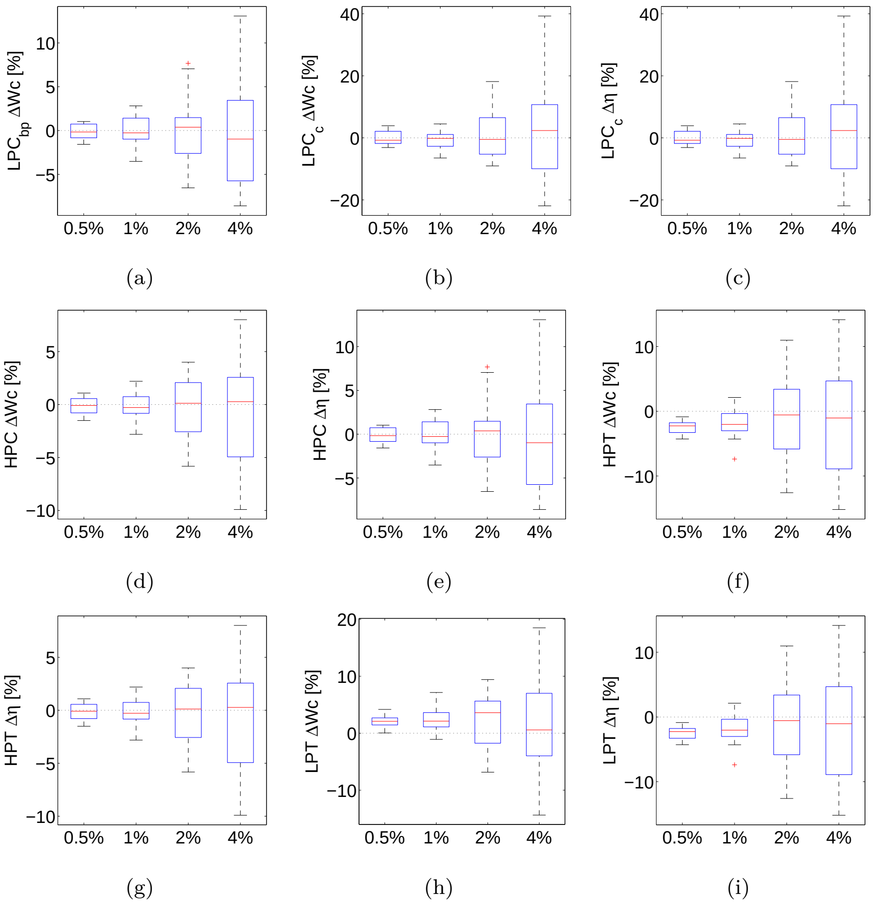


Figure 3.9: *Results of a measurement uncertainty study showing the effect of simultaneously increasing measurement noise levels on each component condition parameter.*

to the results obtained from simulated random uncertainty shown in figure 3.9, they suggest that the combined effect of measurement uncertainty and model error is less then $\pm 1\%$ of the observed performance parameter.

While the results of this feasibility study looked promising, closer inspection revealed some unwanted correlations. The LPC core flow capacity deviation, which was shown in chronological order in figure 3.10(b), is shown in figure 3.11 as function of corrected fan speed. A second degree polynomial fit superimposed on the data points highlights the correlation between the component rotational speed and the estimated component condition deviation. Because the fan rotational speed is directly related to engine power setting, this result suggests that the condition of the LPC core depends on the power setting. In fact component condition parameters should be independent of engine power setting and ambient conditions and should only indicate how component condition is affected by deterioration. While they are not shown for all condition deviations, similar results were also obtained for other compressor components.

This unwanted correlation is caused by inaccurate component maps used for the performance model that forms the basis of the GPA method. The adaptive modeling method used for GPA determines component condition deviations by operating the performance model at the same operating conditions as the measured data and subsequently adapts the condition parameters to match the other measured performance parameters. If a difference exist between the engine and the performance model, this shows up as component condition deviations. Thus instead of identifying component deterioration effects only, the GPA results appear to capture model inaccuracies also. Although GPA with on-wing measured data seems possible, model inaccuracies render the results useless. Therefore, using GPA for on-wing measured performance data requires more accurate models. This aspect is covered extensively in chapter 4.

3.3 GPA challenges for the MRO industry

Component-level condition information obtained from GPA is beneficial for an aero-engine maintenance process. It is particularly useful when an engine failed its post-overhaul performance test or shows unexpected behavior while installed on-wing. But using model-based GPA in practical applications poses several challenges. These challenges, in part, prevent systematic use of GPA in the maintenance process.

The performance models used for model-based GPA introduce some challenges. Although creating a turbofan performance model is in principle a relatively straight-forward process, the accuracy necessary for GPA makes this process more challenging. GPA applications need additional information such as engine-specific sensor locations and geometric data for correctly relating mea-

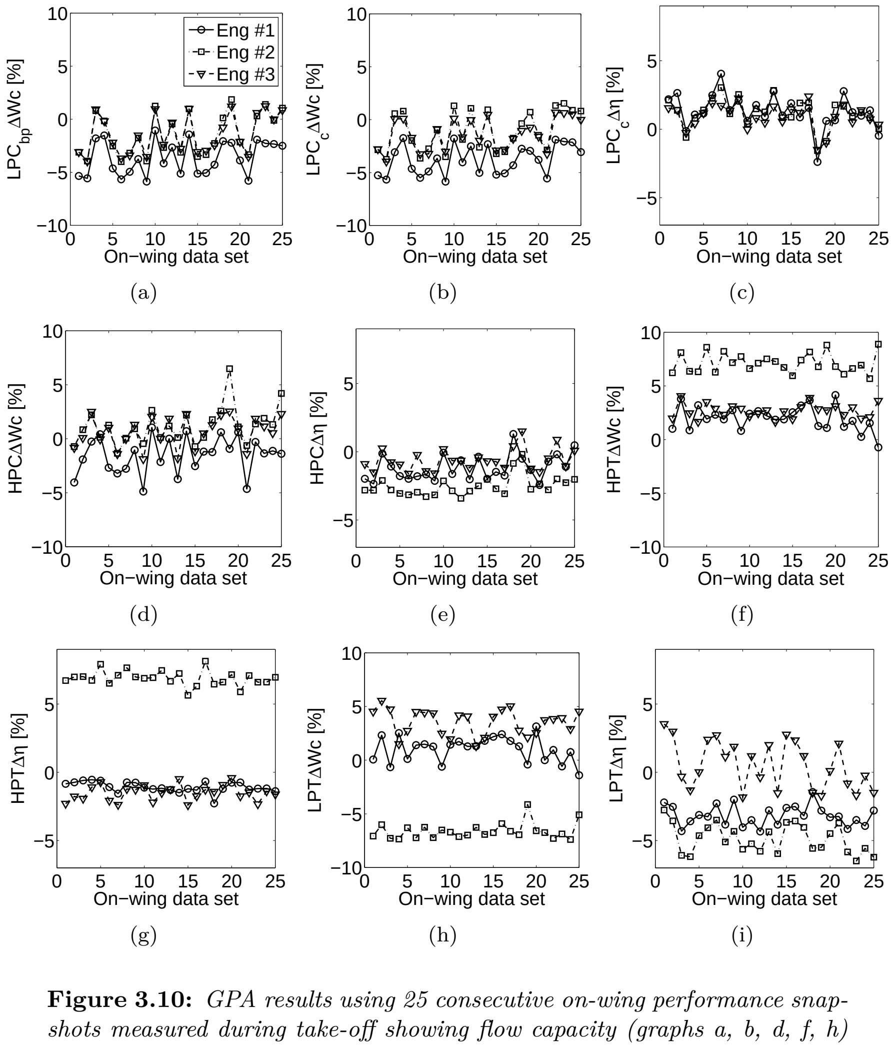


Figure 3.10: *GPA results using 25 consecutive on-wing performance snapshots measured during take-off showing flow capacity (graphs a, b, d, f, h) and efficiency deviations (graphs c, e, g, i).*

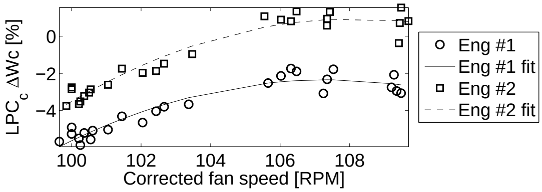


Figure 3.11: *LPC core flow capacity deviation as function of correct shaft speed*

sured performance parameters to simulated parameters. Cycle calculations, necessary for the adaptive modeling calculations, require total (or stagnation) properties. However, at some stations in a gas turbine, static pressure is measured instead of total pressure. Cross flow area information is then necessary to approximate the total properties from the measured static properties. Thus, creating a performance model for GPA purposes requires additional information that would otherwise not be necessary.

One model-related challenge that was encountered was the location of the high pressure turbine temperature sensor of the CFM56-7B. In this engine type the exhaust gas temperature (EGT) sensor is embedded in the nozzle guide vane stage following the first low pressure turbine rotor instead of at the high pressure turbine exit, which is often the case. Because GSP is a 0-D performance model, the state of the working medium is calculated only at component inlet and outlet planes. Consequently, performance parameters measured inside a component cannot be used in the adaptive modeling calculation to determine the component condition parameters. The solution was to split the low pressure turbine, and model it as two separate turbine components that share the same shaft.

The absence of accurate component maps introduces another model-related challenge. Depending on the application, performance model accuracy is not only important at a single operating point, but over a wider range of off-design operating points also. An example is using on-wing measured performance data for GPA. Because the engine power setting is affected by aircraft weight, it varies from one flight to another. For reliable GPA results, the performance model should accurately simulate those varying power settings. Component maps, which are to a large extent responsible for off-design model accuracy, are proprietary to the original equipment manufacturer and generally not available to third parties. In section 3.2.3 it was observed how using alternative component maps affect the GPA results.

Another challenge is related to the absence of measured performance parameters. While some gas path performance parameters are always measured for engine control purposes, others may be optional or are not measured at all. For on-wing condition monitoring applications several sensors may be installed in the gas path. Because of the additional cost related to this optional functionality, some operators do not include these sensors. Additionally, placing a sensor in the gas path may cause unwanted performance issues or may not guarantee long term reliable measurements. When this occurs, the performance model must be set up to handle missing measured performance parameters.

A required adaptation was related to the model layout of the low pressure compressor section. Both the CF6 and the CFM56-7B engine families have a compressor configuration that consists of a fan, a low pressure compressor (booster), connected to the low pressure turbine shaft, and a high pressure compressor, connected to the high pressure turbine shaft. Unfortunately, no performance parameters are measured at the fan-booster interface. As a result, isolation of the fan core and booster performance was not possible. Because both turbomachinery components share the same shaft, they are modeled as a single component in the GSP model. Consequently, the number of condition parameters are reduced, thereby enhancing GPA iteration stability. This required a new component map that combined the performance characteristics of both components together.

Because of limited measured performance parameters, component conditions can not be determined for all turbomachinery components. For the engine families analyzed at KLM Engine Services, special adaptations to the models were necessary to use the available measured performance data. The generic modeling capability of GSP is particularly advantageous to accommodate the required adaptations.

Relating component condition deviations to physical engine problems is another challenge. Maintaining any mechanical device generally means cleaning, repairing, or replacing a defective part. Gas path components consist of a great number of parts, each of which has an important contribution to the overall component performance. If GPA identifies poor efficiency of a gas path component, which of the many parts that form that component needs maintenance?

Finally, possibly the most significant challenge is the absence of integration in the existing data infrastructure. The GSP GPA tool used at KLM is a standalone system that was designed to import the required data from post-overhaul test-cell performance reports. The results could subsequently be saved as a report in a portable document format for future reference. Although this format is independent of application software, hardware, and operating systems, and thereby easy for distribution to clients, further analysis was not possible in a systematic way. Therefore, both importing measured performance data and comparing GPA results of different engines were manual and time-consuming processes. Consequently, the information flows to and from the GPA tool were not optimal for systematic application in the maintenance process.

3.4 Conclusion

This chapter described the experience of using GPA for turbofan diagnostics at an MRO shop. Although GPA allows much more information to be obtained from standard post-overhaul performance acceptance tests, its use is mostly limited to post-overhaul fault diagnostics. The limited availability of in-bound performance data, mainly caused by the additional cost, means that detailed component condition generally cannot be obtained before maintenance.

Several feasibility studies were done to see whether GPA could have more applications within an existing aero-engine maintenance process where engine performance data may be limited and affected by measurement uncertainty. Results of those studies have led to the following conclusions:

- On-wing GPA with GSP has shown good results for turbofan engines with sufficient on-wing measured performance parameters. When GPA results vary due to the effects of random sensor error the arithmetic mean of several component condition parameter deviations can approximate the true component condition provided that the available performance data are measured over a short period during which component condition does not change noticeably as a result of gradual deterioration mechanisms.
- Using on-wing measured performance data for GPA has been identified as a good alternative when measured performance data prior to overhaul are not available. When on-wing measured performance data are used for GPA, however, the GPA tool must provide accurate results over a wider operating range compared to a GPA tool used for analyzing engine performance measured in a controlled engine test cell. This is necessary to account for de-rated take offs.
- When too few on-wing measured performance parameters are available for detailed GPA, adapted-model performance analysis can be used to analyze engines that show abnormal performance. This way GPA is used indirectly for analysis of measured performance parameters that are available.

While results of the feasibility study have demonstrated additional GPA applications that are beneficial for the aero-engine maintenance process, bottlenecks have been identified that need to be resolved for embedding and systematically using GPA in the maintenance process.

- For model-based GPA in general accurate component maps enable more accurate component condition estimations. However, accurate component maps are essential for reliable GPA results when using on-wing performance data with varying engine power settings. Without sufficiently accurate component maps, GPA results obtained with on-wing measured performance data represent a combination of component deterioration, model error and measurement uncertainty. Such results offer little value to aero-engine maintenance.

CHAPTER 4

Improving GPA reliability

Abstract

This chapter presents methods for improving the accuracy and reliability of GPA results. First the major sources of uncertainty are discussed and the effects of random measurement uncertainty are quantified by means of the Monte Carlo method. To improve performance model accuracy a component map tuning method is presented that requires an approximate component map, on-wing measured performance data and the adaptive modeling capability of GSP. Thereafter the importance of correct model calibration on GPA results is discussed and an off-design model calibration method is presented. Finally, the problem of selecting reference data from operational engines for GPA application is discussed. Two methods are presented that use multiple reference data sets to obtain a better estimate of the actual component condition and the corresponding uncertainty of this estimate.

The content of this chapter is based on:

Verbist, M.L., Visser, W.P.J., Pecnik, R., and van Buijtenen, J.P., **Component map tuning procedure using adaptive modeling.** ASME Turbo Expo 2012. GT2012-69688

Accurate and reliable GPA results are essential when GPA is used in the aero-engine maintenance process. When incorrect diagnostic information obtained by means of GPA is used for planning maintenance work scopes, the resulting performance improvement may be less than expected. This imposes financial risks for an engine repair facility that uses GPA in its maintenance process.

Model-based GPA tools use a gas turbine performance model and measured engine performance parameters for estimating gas path component condition deviations relative to baseline condition. Because there may be differences between the performance model and the engine being analyzed, a model calibration step is necessary. The GSP adaptive modeling (AM) component that is used for this study can use arbitrary reference engine data sets for this calibration step prior to model adaptations. However, the engine model and the performance data may contain errors that propagate through the AM calculation [43]. Depending on the type of error present, GPA results may contain random errors and systematic errors—an off-set relative to the true but unknown value being measured. This reduces the accuracy and reliability of a GPA tool.

This chapter discusses several issues that affect model-based GPA results. It presents methods for improving the accuracy and reliability of model-based GPA results such that they can be used for systematic application in the aero-engine maintenance process.

4.1 Uncertainty effects

An important aspect affecting GPA accuracy and reliability is measurement uncertainty. Measurement uncertainty may be classified into two groups: *random uncertainty* and *systematic uncertainty*. Effects of random uncertainty can be revealed by means of repetitive measurements and can be characterized with statistical analysis[63]. Sensor noise, unstable engine operation resulting from small changes in inlet flow conditions, variable geometry settings, and thermal expansion of components are sources of random uncertainty. Systematic uncertainty is a form of measurement uncertainty where the measured value has a consistent error (offset) with respect to the true but unknown value. Such errors may be caused by sensor bias, incorrect sensor position, and model errors. The study presented in this section focuses solely on the effects of random uncertainties.

Gas turbine performance models use deterministic algorithms [47]. For model-based GPA this means that a particular input always generates the same output, that is, a given performance model and a given performance data set always yield the same GPA results. If the input data contain uncertainties, the output too will contain those uncertainties. Therefore, performance data from a single snapshot are not sufficient to assess the effects of sensor error on GPA results through statistical analysis.

4.1.1 Unsteady engine performance

Gas turbine performance models are used for steady-state and transient performance prediction. Although GPA has been demonstrated with transient performance data [27, 34, 39], most GPA tools are developed for analysis of steady-state performance data.

Steady-state performance in a controlled test environment is achieved by operating a turbofan engine at constant power until all measured performance parameters are stabilized. The performance data obtained at those steady-state conditions are excellent for GPA. However, during take-off a turbofan engine operates at a take-off power setting for a few minutes during which the aircraft first accelerates from stationary conditions followed by an increase in altitude at an approximately constant climb speed. To conserve the engine life time, power is then reduced when a certain altitude and speed are reached. These variations prevent the engine to reach true steady state performance during this operational phase. When steady-state conditions are assumed but are not achieved, small performance deviations may lead to component condition estimation errors.

4.1.2 Secondary flow effects on adaptive modeling

Turbofan engines are designed such that a fraction of the compressed core engine flow, often referred to as *bleed air*, is redirected from the core flow path for cooling and pressurization applications. A distinction can be made between compressor bleed air used for engine-related applications such as turbine cooling, and so-called customer bleed air that is used for aircraft-related applications such as cabin pressurization and air conditioning. While most of the bleed air for turbine cooling purposes returns to the main flow path before or during expansion in the low pressure turbine, customer bleed-air does not return to the gas path. Depending on the amount of customer bleed air, this can be a significant loss of energy from the thermodynamic process occurring in the turbofan.

Measurements or flow schedules for bleed air are not available for operational engines. However, the engine Type Certificate Data Sheet (TCDS) specifies maximum limits for several bleed flow locations. This information, which is shown in table 4.1, was used for creating a CF6-80C2 model that included internal cooling flows and customer bleed flows. This model was created by iteratively varying the cooling mass flow fractions to match performance data measured in a test cell. Because the internal cooling flows are not actively controlled, they were modeled as fixed mass flow fractions. During operation in a test cell, customer bleed flow ducts are closed. The effects of customer bleed on engine performance were analyzed after values for the internal cooling flow were established.

Table 4.1: *This table lists the maximum permissible mass fractions of high pressure compressor bleed flows for the CF6-80C2 engine. Different limits are defined for engines with a Full Authority Digital Engine Control (FADEC) and engines with a Power Management Control (PMC).*

Bleed location	CF6-80C2 FADEC	CF6-80C2 PMC
Stage 7 HPC	-	-
Stage 8 HPC	8.8%	8.8%
Stage 11 HPC	1.5%	1.5%
Stage 14 (CDP):		
Steady state @ TO rating	5.0%	5.0%
Steady state @ MC or below	10.0%	
Transient @ MC or higher	7.0%	
Steady state between 80% N2 and MC		10.0%
During accelerations @ 80% N2		7.0%
Operating at 80% N2 or below		12.0%

To analyze the effects of customer bleed flows and turbine cooling flows on the adaptive modeling calculation, several mass fractions of customer bleed were simulated. Mass fractions for the cooling flows remained constant. The resulting performance parameters were analyzed with a diagnostic model for the CF6-80C2 that contained no bleed and cooling flows. The results for several levels of customer bleed are shown in figure 4.1a. These results show that customer bleed flow significantly affected the adaptive modeling results when bleed flows were *not* taken into account.

Effects of customer bleed flows were analyzed with a simulated HPC deterioration also. For this analysis an HPC efficiency deterioration of -4% was simulated. The results presented in figure 4.1b show that the value of the simulated component deterioration was still correctly identified for low levels of customer bleed. However, for increasing levels of customer bleed flows the simulated HPC deterioration blended into the incorrectly estimated component condition deviations that resulted from the customer bleed. The effects of turbine cooling flows can also be observed in figure 4.1. At 0% customer bleed flow both figure 4.1a and figure 4.1b show small component condition deltas. But these deviations are much smaller than those resulting from customer bleed flows.

For an accurate estimate of engine condition parameters, all factors that significantly affect measured performance parameters should be included in the analysis. When information regarding those effects is neglected, results of the adaptive modeling procedure may still match measured engine performance. But the resulting condition parameter deviations will compensate for the omitted factors that affect performance parameters. Therefore, neglecting significant factors such as customer bleed may lead to incorrect component condition estimations.

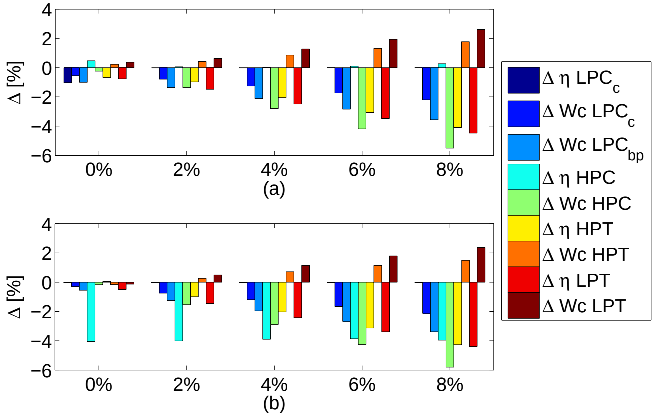


Figure 4.1: *Customer bleed effects on estimated component conditions for increasing bleed air mass fraction. Figure (a) contains results for an engine with no deterioration. Figure (b) contains results for an engine with simulated HPC efficiency deterioration;* $\Delta\eta_{HPC} = -4\%$.

4.1.3 Measurement error

When random uncertainties are known for a set of measured performance parameters, the Monte Carlo method can be used to obtain statistical information about the effects of random error propagation. Statistical data available for the sensors were used as input for this analysis. A list of this sensor information is presented in table 4.2. The indicated errors represent a 95% confidence interval, i.e., 2σ. A set of performance parameters was generated for an engine with no condition deterioration. Based on the available sensor information and the simulated performance parameters, the MATLAB® *randn* function was used to generate a 1500 data sets with a normal distribution.

To analyze the effects of sensor error propagation, simulated sensor errors were added to measured performance parameters of the engine used for analysis. Gas path analysis was used for quantifying the effects of the simulated sensor

Table 4.2: *Sensor error accuracies that were used for the error propagation analysis [17].*

Sensor	Range	2σ
Barometer pressure	11-16 psi	$\pm$ 0.02%
Pneumatic pressure	$\pm$ 1 psid	$\pm$ 0.15%
	$\pm$ 5 to $\pm$ 750 psid	$\pm$ 0.05%
Thermocouples	0-1000 °C	$\pm$ 0.5°C
RTD	-50 to +200 °C	$\pm$ 0.2°C
Frequency	1 to 100 kHz	$\pm$ 0.2%, >400 Hz
Fuel flow	400-40000 pph	$\pm$ 0.25%

errors. The unperturbed set of measured performance parameters served as reference engine performance for these calculations. This approach eliminated any potential systematic errors that may otherwise affect the GPA results.

Component condition parameter deviations were determined for each set of perturbed performance parameters. The convergence of the Monte Carlo analysis was observed by analyzing the development of the sample mean ($\bar{x}_n$) and standard deviation (σ_n) in relation to the number of trials. The lowest rate of convergence was observed for the isentropic efficiency deviation of the fan core flow ($\Delta\eta_{LPC_c}$). Graphs of the sample mean and standard deviation of $\Delta\eta_{LPC_c}$ are presented in figure 4.2. The graphs show that both ($\bar{x}_n$) and (σ_n) converge within the 1500 trials used for this analysis. Figure 4.3 presents the probability distributions obtained from the Monte Carlo analysis. Additionally it also presents the values for $\bar{x}_n$ and σ_n for each condition parameter.

The results of the error propagation analysis presented in figure 4.3 show that the values for sample mean converge to zero deviation for all component condition parameters calculated, that is, $\bar{x}_n \approx 0$. This corresponds with the performance parameters used for the Monte Carlo analysis of an engine with no condition deterioration. The narrow probability distributions shown in figure 4.3 suggest that the effect of random sensor errors on the adaptive modeling calculation results are relatively small. The exception was the standard deviation for $\Delta\eta$ LPC$_c$ with $\sigma_{\Delta\eta LPC_c} = 0.5\%$. The reason for this relatively large standard deviation was the lack of a temperature measurement in the fan bypass outlet duct or a pressure measurement at the LPT outlet. Consequently, the numerical procedure could not estimate a value for $\Delta\eta$ LPC with similar accuracy compared to the other components.

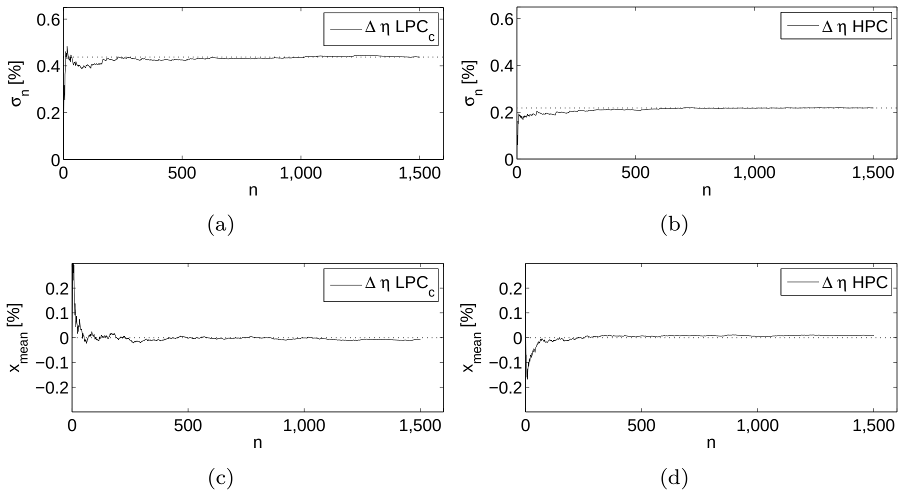
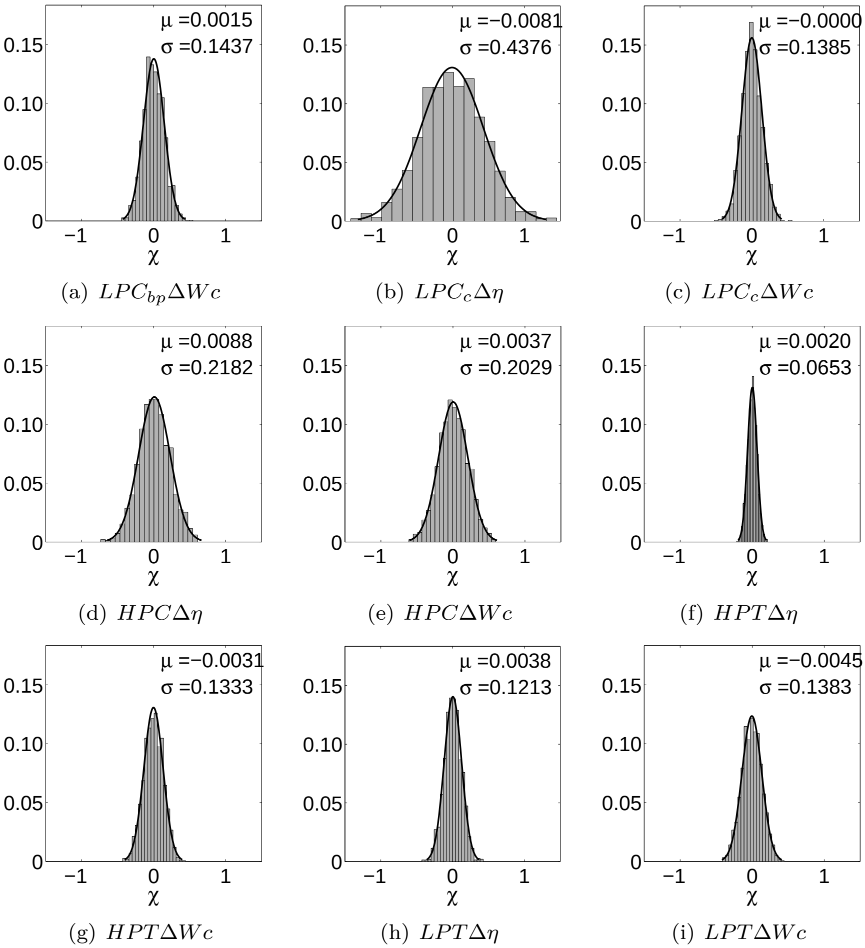


Figure 4.2: *The graphs show the convergence of standard deviation (σ_n) and sample mean (x_{mean}) of the LPC core and HPC efficiency estimation for an increasing number of trials. These results suggest that between 500 and 1000 trials are sufficient for reliable σ_n and x_{mean} estimates*

4.2 Component map tuning

Gas turbine performance models use the conservation equations of energy, mass and momentum for obtaining equilibrium operating points. Component maps are used to describe off-design behavior of individual gas path components in performance models. These maps are a description of the aero-thermodynamic behavior of a gas path component. This behavior is captured in correlations between performance parameters such as pressure ratio and rotor speed, and mass flow and rotor speed. The accuracy of component maps has a direct effect on the performance model accuracy. Component maps contain within them a complete performance description of the component they belong to, which is directly linked to the component design. Consequently, original equipment manufacturers (OEMs) consider them proprietary and the maps are usually not available outside the OEM environment.

In academia and the industry, performance models are often developed independent of the OEMs. Because component maps are not usually available, several methods have been developed to reverse-engineer these maps from existing maps and operational performance data. Generally, as a first approximation, maps for similar gas turbine components available in the public domain are scaled to a known reference operating point [31, 61]. Performance simulation



(a) $LPC_{bp}\Delta Wc$ (b) $LPC_c\Delta\eta$ (c) $LPC_c\Delta Wc$

(d) $HPC\Delta\eta$ (e) $HPC\Delta Wc$ (f) $HPT\Delta\eta$

(g) $HPT\Delta Wc$ (h) $LPT\Delta\eta$ (i) $LPT\Delta Wc$

Figure 4.3: *This figure shows the probability density functions (PDFs) for the condition parameters obtained by means of the Monte Carlo method. All PDFs have a normal distribution with a zero mean (μ), which confirms no condition deviations in the simulated data. The standard deviation (σ) indicates the sensitivity to the effects of random uncertainty.*

accuracy depends on how well the scaled maps represent the correlations of the actual components for which they are used. Therefore, often additional map tuning is required to better match component performance. Several map modification techniques are currently in use. Some methods take the laws of physics into account [31–33], while others use different approaches such as neural networks, genetic algorithms, and morphing techniques [30]. The scaling methods all aim to approximate the unknown off-design performance of a component as close as possible.

In addition to condition monitoring, adaptive modeling has been used also for improving model accuracy at reference performance [40, 61]. Component map tuning through adaptive modeling was identified in earlier work published by Lambiris et al. [35]. By fine-tuning the engine design parameters to match a specific engine operating point, model accuracy can be improved.

This section presents a component map tuning procedure that combines the adaptive modeling capability of the Gas turbine Simulation Program (GSP) [46] with on-wing measured performance data. It builds on concept of model tuning using adaptive modeling presented by Lambiris et al. [35] by extending the concept to off-design engine performance. The objective of this study was to tune available component maps to a level of accuracy such that on-wing measured performance data can be used for GPA.

4.2.1 On-wing measured performance data

For this study, on-wing take-off performance data of CF6-80C2 engines were used. Although performance data measured in a controlled test cell environment would be of better quality, insufficient test cell performance data were available. Several engines would then be necessary to collect sufficient performance data. Since each engine would have a slightly different condition, this would add an additional uncertainty factor to the tuning process. Therefore, we decided to use on-wing measured performance data. Because on-wing performance data were available from the first flight after overhaul, the on-wing engine condition could be compared to the engine condition estimated with its test cell data.

However, during performance acceptance tests in an engine test cell, turbofans are operated at 4 specific corrected power settings to verify correct performance: ground idle, flight idle, maximum continuous, and take-off power. Because of this approach, performance data from the test cell were available only at these discrete power settings. In contrast, during on-wing operation, atmospheric conditions and power setting may vary considerably among flights. De-rated take-offs are frequently used to conserve the remaining engine life. Air temperature between take-offs may vary in excess of 30 Kelvin also. Consequently, depending on the necessary take-off power, the corrected shaft speeds may vary in excess of 10%. These variations provided measured performance

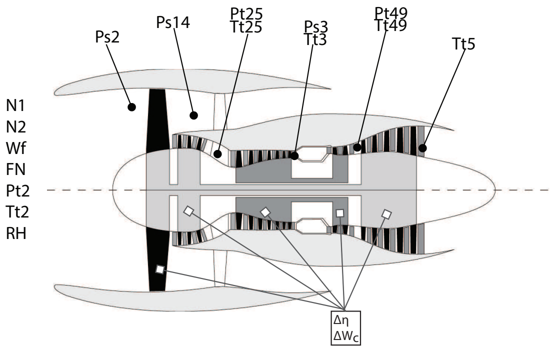


Figure 4.4: *This figure shows the measured performance parameters available for adaptive modeling with test cell and on-wing performance data. The objective of GPA is to estimate the changes of η and Wc for as many parameters as possible. Note that during on-wing performance thrust (FN) and relative humidity (RH) are not measured.*

data over a wider range of power settings and operating conditions during take-off compared to test cell performance. This way, the use of on-wing measured performance data enabled map tuning over a wider range of power settings compared to engine performance measured in a test cell.

The CF6-80C2 engines used for map tuning procedure were equipped with an extended condition monitoring sensor package. The approximate sensor locations are shown in schematic of a turbofan in figure 4.4. During on-wing operation relative humidity (RH) and engine thrust (FN) are not measured. When direct thrust measurements are not available, fan bypass static outlet pressure (Ps14) serves as a good alternative to determine overall engine power [70]. Because relative humidity was not measured during on-wing operation, standard day conditions are assumed for the analysis of on-wing performance data, i.e., RH = 60%. The effects of relative humidity variation on sea level take-off performance are relatively small and are not considered in this study.

The engines for which on-wing performance data were available were installed on Boeing 747-400 aircraft. For those aircraft the auxiliary power unit takes care of air conditioning to maximize available power during take-off. Fortunately, this is also the flight phase during which the on-wing performance measurements are recorded. The customer bleed flows could, therefore, not affect the map tuning procedure.

4.2.2 Tuning procedure

When model-based GPA is used to estimate component condition, it is assumed that the engine model–and corresponding component maps–are accurate and that gas path component deterioration is the sole cause of estimated condition parameter deviations. However, for the component map tuning procedure presented in this section the inverse was assumed. Now it was assumed that the available performance data were from engines with known and constant condition, and that any estimated condition parameter deviation is caused by model errors.

The adaptive modeling calculation used for this study can be described as a series of two calculation steps. First, to obtain an accurate baseline model, the engine model is tuned to measured performance data of a reference engine. During this step the reference model reference point is matched to measured performance parameters with so-called calibration factors. In the second step, map modifiers are used to adapt the baseline reference model to the measured performance parameters of the engine that is analyzed. A detailed description of this procedure is given by Visser et al. [74]. The resulting component condition parameter deviations are therefore always relative to the performance of the reference engine.

For the map tuning process on-wing measured performance data were used from engines that had undergone overhaul and were equipped with an extended sensor package. Therefore, apart from detailed post-overhaul test cell performance data, on-wing performance data were available also. The available on-wing performance data allowed engine condition estimation with the same level of detail compared to test cell data. Moreover, on-wing performance data were available from the first flight after maintenance. This allowed detailed engine condition monitoring while installed on-wing. Depending on the engine type, turbofan engines can operate on-wing for a period of approximately two up to more than seven years. During that time gradual component deterioration occurs. However, to operate on-wing for a long period of time, component condition deterioration should be minimal in a relatively short time interval. Therefore, as long as the period for which data were available was not too long, the constant engine condition assumption is valid. In addition, by using performance data from the initial flight after maintenance, no condition deviations could occur between test cell engine test and on-wing operation.

The component maps were tuned such that the estimated component conditions were both equal to the known condition, and constant for the available performance data. Moreover, it was assumed that other error sources had minimal effect on estimated component condition deviations compared to inaccurate component maps. To substantiate this assumption, the effects of compressor bleed flows and measurement uncertainty were analyzed. These aspects, which were suspected to have the biggest impact on the map tuning procedure, were covered earlier in this chapter.

Component maps were tuned by re-labeling constant speed lines. Speed line re-labeling modified the correlations that existed between shaft speed and corrected mass flow, and isentropic efficiency and corrected mass flow. The modified correlations affected the component map interpolation results that form an integral part of steady state operating point calculations in gas turbine performance models. This led to different off-design model performance, thereby affecting the estimated component conditions of the adaptive modeling calculation. The tuning procedure was performed by iteratively re-labeling individual speed lines and calculating the effect on the estimated component conditions. From the results of each re-labeled speed line, the root mean square (RMS) value was determined. For each speed line, the RMS values were plotted against the speed line label. By curve-fitting a second order polynomial through the RMS values for each speed line, an optimal speed line was determined, that is, a speed line that yielded a minimum RMS value. This iterative routine was performed manually for each speed line that affected the off-design model performance. The original maps were tuned until the RMS value of each component condition, estimated with on-wing performance data, converged to a minimum value.

4.2.3 Results and discussion

Compressor maps were tuned by using a technique called speed-line re-labeling. This section present the results of the tuning procedure that was done for three compressor maps of an engine model representing the General electric CF6-80C2 engine. For the engine used, on-wing take-off performance data were available for a period of 55 days. In total, 93 consecutive take-off snapshots were used to tune the compressor maps.

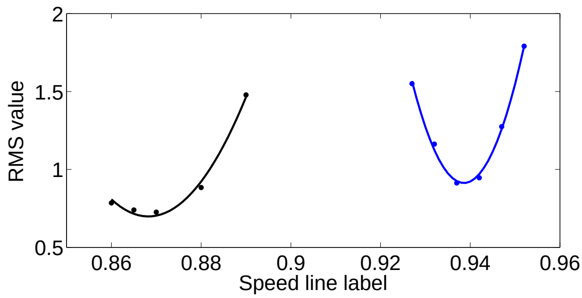


Figure 4.5: *The RMS values and the corresponding best-fit curves plotted against the speed line label for the combined fan core and booster component. These graphs indicate that a minimum error would be obtained for normalized speed line labels of 0.87 and 0.94.*

The map tuning procedure was performed iteratively. After a speed line was re-labeled, the condition deviations were determined with the adaptive modeling procedure. For each set of condition deviations an RMS value was calculated. In figure 4.5, the RMS values are plotted against the corresponding speed line. To determine the speed line values that resulted in the optimal RMS value, a best fit curve was generated. The position on the horizontal axis for which the first derivative of the best-fit curve was 0, was chosen as the optimal speed line label for the iteration step. This procedure performed for each speed line that affected the adaptive modeling calculations with the on-wing performance data. It was repeated until the optimal value for each speed line converged.

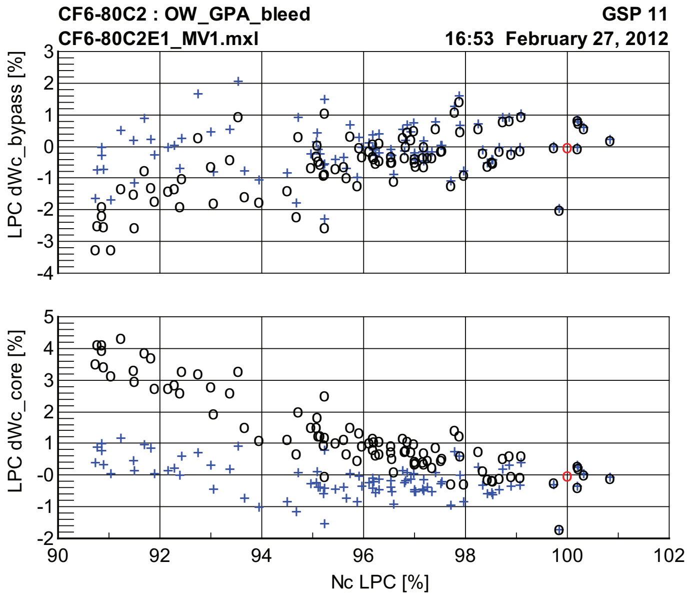


Figure 4.6: *Fan core and fan bypass mass flow capacity condition deviations graphed against the corrected LPC (N1) shaft speed. o-markers show the results obtained with original maps, +-markers represent the results obtained with the tuned maps.*

Adaptive modeling results with on-wing measured performance data for the original and tuned map are presented in figures 4.6 and 4.7. Figure 4.6 contains the results for the flow capacity deviations (dWc) for the combined fan core and booster flow (LPC_c) and the fan bypass (LPC_{bp}) flow. Figure 4.7 contains the results for the flow capacity deviations (dWc) for the HPC. The o-markers indicate the results of the adaptive modeling calculation with the original maps.

The flow capacity deviations for the LPC core and bypass flow show a strong correlation with the corrected LPC shaft speed (Nc LPC) in figure 4.6. A similar correlation was observed between the HPC flow capacity deviation

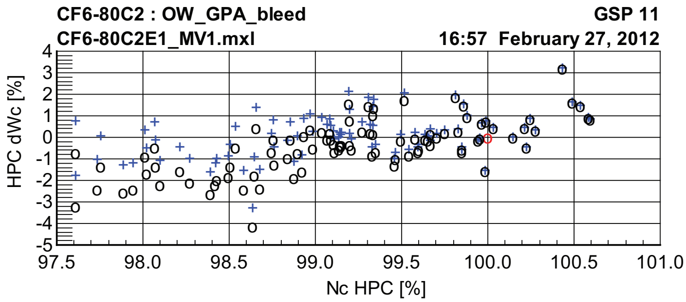


Figure 4.7: *HPC mass flow capacity condition deviations graphed against the corrected HPC (N2) shaft speed. o-markers show the results obtained with original maps, +-markers represent the results obtained with the tuned maps.*

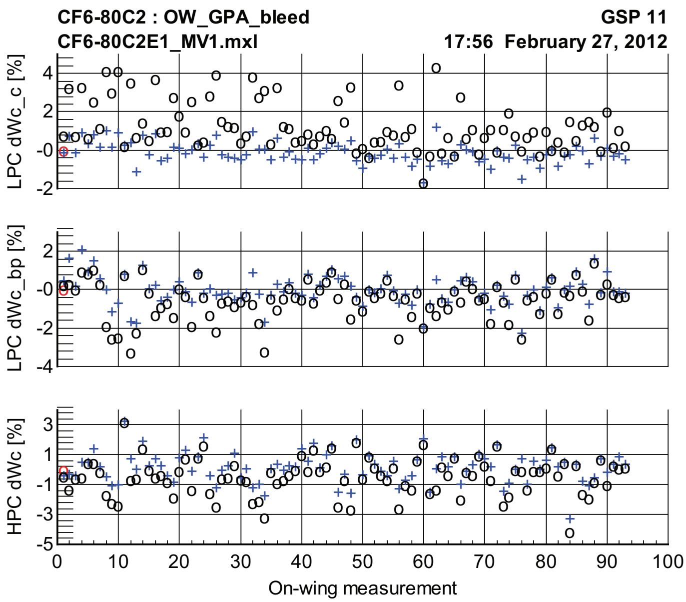


Figure 4.8: *LPC core and bypass mass flow capacity condition deviations graphed in order of measurement. o-markers show the results obtained with original maps, +-markers represent the results obtained with the tuned maps.*

and the HPC shaft speed (Nc HPC) in figure 4.7. While small deviations are possible when estimating gas path component condition from performance data obtained at different power settings [44], strong correlations as those observed in figures 4.6 and 4.7 should not be present. These correlations suggest that the flow capacity condition parameter depends on the shaft speed. Component condition parameter deviations should indicate how the component condition deviates relative to the reference engine used. These, and other condition parameter deviations, should be independent from engine power setting, and ambient conditions. The correlation between the flow capacity deviation and corrected shaft speed indicated that the correlations between the corrected mass flow and shaft speed in the compressor maps do not accurately represent the CF6-80C2 components.

The +-markers illustrate the results obtained with the tuned compressor maps. The flow capacity condition deviations obtained with the tuned maps show no clear correlation with the corrected shaft speed of the component. The improvements resulting from the tuned compressor map are more pronounced for the LPC than for the HPC. The reason for this was that the original compressor map that was used for the CF6-80C2 HPC was a compressor map for the HPC of an older CF6 engine. The compressor maps for the LPC bypass and LPC core were obtained from the public domain. The initial maps for the LPC did not accurately represent the correlations that exist between the corrected mass flow and the shaft speed. The tuned maps have a better representation of these correlations.

Although the general pattern improved, significant scatter remains present in the calculated component conditions shown in figures 4.6 and 4.7. Fine tuning the compressor maps did not reduce the amount of scatter. In figure 4.8 the component deterioration is shown in chronological order also. These results show that the remaining scatter of flow capacity deviations was not caused by time dependent component deterioration during the period for which the on-wing measured data were available. The graph remains essentially flat, suggesting constant component condition.

4.3 Performance model calibration

Component condition deviations are calculated relative to a reference (or baseline) engine. Differential GPA methods use a performance model to calculate the effects of condition parameter deviations on performance parameters. The performance differences between the reference engine and the engine being analyzed, both operating at the same power setting and atmospheric conditions, are caused by component condition deterioration, measurement error, engine-to-engine variation and model error. This section focuses on model error and the reduction thereof by means of model-calibration.

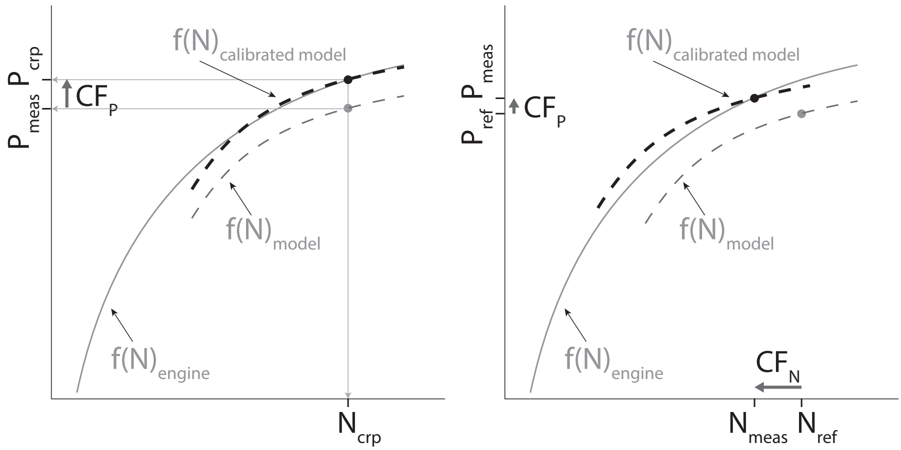
When differences remain between model performance parameters and reference engine performance parameters, these propagate through the calculations and introduce errors in the estimated component condition deviations. That is, condition deviations that are not caused by actual component deterioration, but by model error. To remove this source of errors, a model calibration step is used for eliminating any differences between the reference engine and the performance model. This calibration step is also useful to compensate for inherent engine-to-engine variations when different reference engines are used for GPA.

Two methods used for performance model calibration are *single-point calibration* and *multi-point calibration.* The single-point calibration method, which is implemented in GSPs AM component, uses performance data from a single operating point as a reference for performance model calibration. The multi-point calibration method [19, 62, 73] uses multiple off-design operating points for model calibration. If a gas turbine performance model closely matches real engine performance within the desired operating range, the accuracy obtained through single-point calibration is sufficient for practical GPA applications. In the remainder of this thesis, single-point model calibration that is used in this study is referred to as model calibration.

$$f_{c_i} = \frac{P_{i_{ref}}}{P_{i_{mod}}} \tag{4.1}$$

In the AM calculation used for this research work, model calibration is done in the following way. The performance model is operated at the same ambient conditions as the reference engine. The ratio between model performance and reference engine performance is used for calculating *Calibration Factors* (CFs) as shown by equation 4.1. During the calibration step this is done for all measured performance parameters. $P_{i_{ref}}$ is a performance parameter of the reference engine and $P_{i_{mod}}$ is the same performance parameter of the model. The CFs are subsequently used in the AM calculation process for scaling each measured performance parameter prior to the actual model adaptation step. Figure 4.9(a) shows a graphical representation of the model calibration step.

When off-design performance data are used as reference, the resulting CFs often deviate from 1 because of small differences between the reference engine and the performance model, especially for the power setting calibration factor. The model calibration method used up to this point assumed that reference performance data were always measured at, or close to, model design point power setting. This assumption is valid when performance data are measured in controlled test facilities where the gas turbine is operated at constant corrected power settings and allowed to reach steady state performance. An important consequence of this assumption is that calibration factors are also calculated for the engine power setting parameter. This way, differences between performance parameters are eliminated regardless if the differences resulted from



(a) design point model calibration at equal power settings

(b) design point model calibration at unequal power settings

Figure 4.9: *These figures show the effect of design point model calibration when the model power settings and the reference engine power setting are equal 4.9(a) and when they differ 4.9(b). Although model calibration leads to a good match between the engine model (dashed lines) and reference engine (solid line) for equal power settings, the results for different power settings shows significant differences when the power settings used during model calibration are different. While the calibration factor (CFp) in figure 4.9(b) may be small when compared to figure 4.9(a), the power setting calibration factor* $\neq 1$ *leads to incorrectly calibrated model.*

different engine power setting or small differences between the model and reference engine. While this approach leads to reasonable results for small power setting differences, larger differences lead to incorrect model calibration, which may result in incorrect GPA results. This effect is shown graphically in figure 4.9(b).

Using the design point model calibration method with off-design reference data can lead to the following scenario. Assume that performance data, measured at 95% power setting, are used as reference, whereas the model was designed and tuned at 100% power. Because of the different power setting, most CFs differ from 1 and a CF of 0.95 is obtained for the power setting parameter. Now, assume the data set that need be analyzed are measured at 101% power. During the actual AM calculation step, each performance parameter of the data set is first scaled with their respective CF. While an exact match between the model and reference data will be obtained for the calibrated power setting, errors may result at other power settings. This is effect is shown by the mismatch between the calibrated model and reference engine performance in figure 4.9(b). For the power setting parameter in this example it means that the actual power setting used for the analysis is: $0.95 \cdot 1.01 \approx 0.96$. In other words, the AM calculation will try to match the measured performance parameters from 101% power to model performance at 96% power level, which leads to incorrect component condition estimations. Thus design point model calibration can only be used reliably when both the performance model and the reference engine operate at the same 'design' power setting. In reality this is hard to achieve and there are always differences between the performance model and performance data used as reference for model-based GPA.

4.3.1 Off-design model calibration

To use reference data sets of a wider range of power settings an off-design model calibration method has been developed and implemented in the AM component. For this method, the assumption that the reference data were always measured at, or close to, model design point power setting was discarded. Instead, with this approach the model is calibrated at the same ambient conditions and power setting as the available reference data set. The off-design calibration method is shown graphically in figure 4.10. This capability is useful for the analysis of on-wing measured performance data obtained during take-off. In addition, it provides a flexibility in selecting healthy engines for which operational data are available to serve as reference.

Methodology

To study the fitness of both model calibration methods for practical GPA application, simulated performance data were used. Using simulated data instead of real engine data eliminated unwanted effects such as model inaccuracies and measurement uncertainty that also influence the GPA results. This way, the effect of the model calibration method was isolated which allowed for correct analysis.

With the performance model of the CF6-80C2 engine, performance data were generated in a range representing take-off power. From the available on-wing data for several engines it was observed that the power setting, indicated by the observed fan speed, varied between 2990 and 3610 RPM. Since ambient conditions are taken into account during the calibration step, varying the inlet temperature, pressure, and relative humidity for the simulated data set was not necessary. Thus, performance data were simulated for an engine without deterioration operating at standard day atmospheric conditions and a fan speed range between 2985 and 3615 RPM.

The CF6-80C2 performance model was designed using reference engine performance data measured in a controlled engine test cell. The reference engine

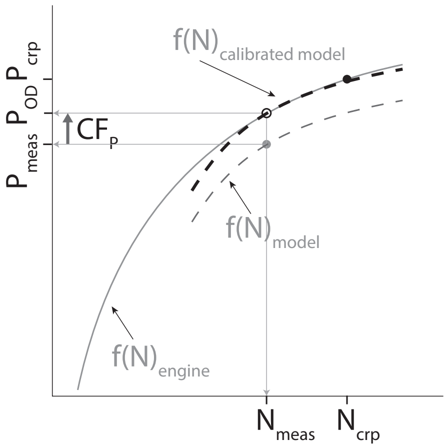


Figure 4.10: *Graphical representation of the off-design model calibration method. The overlap between the calibrated model (dashed lines) and the reference engine (solid line) shows that by calibrating the model at the same ambient conditions and power setting as the reference data set, a close match can be obtained over a relatively wide range of power settings.*

	calibration method	
power setting [rpm]	design point	off-design
3110	case 1	case 4
3285	case 2	case 5
3525	case 3	case 6

Table 4.3: *Overview of the six cases that were used to analyze the effects of design point and off-design model calibration*

fan speed from that data set was 3525 RPM, or 107.47 % of the design fan speed. The generated data set was analyzed six times, using the two calibration methods, design point and off-design calibration; and three different reference engine power settings expressed as 3120, 3280, and 3525 fan rpm. These speeds correspond to 95 %, 100 %, and 107 % of the design fan speed. The 107% power setting was used to ensure that design point calibration was executed at the same power setting for which the performance model was tuned. An overview of the six different cases is shown in table 4.3.

4.3.2 Results and discussion

Because take-off performance of CF6-80C2 model without component deterioration was simulated, the GPA results from those data should contain no condition deviations. Analysis of the six cases shown in table 4.3 generated 12 condition deviation trends for each gas path component. The calibration factors that were calculated for each case are presented in table 4.4. To limit the number of graphs, the differences of both calibration methods are illustrated for the core engine components only. Correctly estimating these component condition deviations is important because in practice these components deteriorate the most and are often the main cause of engine performance degradation.

Design point model calibration results

Cases 1, 2, and 3 were analyzed with the design point model calibration method. The calibration factors of these three cases are presented in the first three data columns of table 4.4. The deviating calibration factors for cases 1 and 2 indicate that the reference data and the engine model do not match.

The GPA results, presented in figure 4.11, show the HPC and HPT efficiency and flow condition deviation trends. Those results show that only case 3 correctly reflects the simulated engine condition, i.e., no condition deviations. Case 1 and case 2 both resulted in non-zero condition deviations.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
N_1	0.888	0.932	1.000	1.000	1.000	1.000
Ps_{14}	0.915	0.952	1.008	1.007	1.008	1.008
Tt_{25}	0.930	0.957	1.001	1.002	1.001	1.001
Pt_{25}	0.795	0.871	1.003	1.006	1.005	1.003
Tt_3	0.911	0.943	1.002	1.003	1.002	1.002
Ps_3	0.726	0.818	1.007	1.010	1.009	1.007
N_2	0.925	0.949	0.999	0.999	0.999	0.999
Tt_{45}	0.891	0.926	0.999	0.999	0.999	0.999
Pt_{45}	0.720	0.812	1.001	1.004	1.004	1.001
Tt_5	0.898	0.926	0.997	0.997	0.997	0.997
Wf	0.646	0.750	0.989	0.991	0.991	0.989

Table 4.4: *This table present the calibration factors obtained for the three reference data sets that were calibrated with two calibration methods.*

The condition estimation error for the HPC was much larger than the estimation for the HPT. The reason for this effect may be explained as follows. Because of choked flow in the HPT during maximum power, the operating point in the HPT component map is fixed, that is, both the pressure and the corrected flow are constant. Consequently only small HPT condition variations will lead to thermodynamically feasible steady state operating points. This leads to smaller estimated component condition deviations.

The results of cases 1 and 2 demonstrate that off-design reference data in combination with the design point calibration method may lead to incorrect component condition estimations. Moreover, the condition estimation error increases for increasing power setting difference between the reference engine data set and the data set used for analysis. This behavior can be explained by considering figure 4.9(b). Even though the resulting calibration factors may deviate significantly from 1, for power settings close to the calibrated point the model does match engine performance. As power settings move away from this point, model error introduces differences that appear as component condition deviations in the GPA results, leading to incorrect condition estimations.

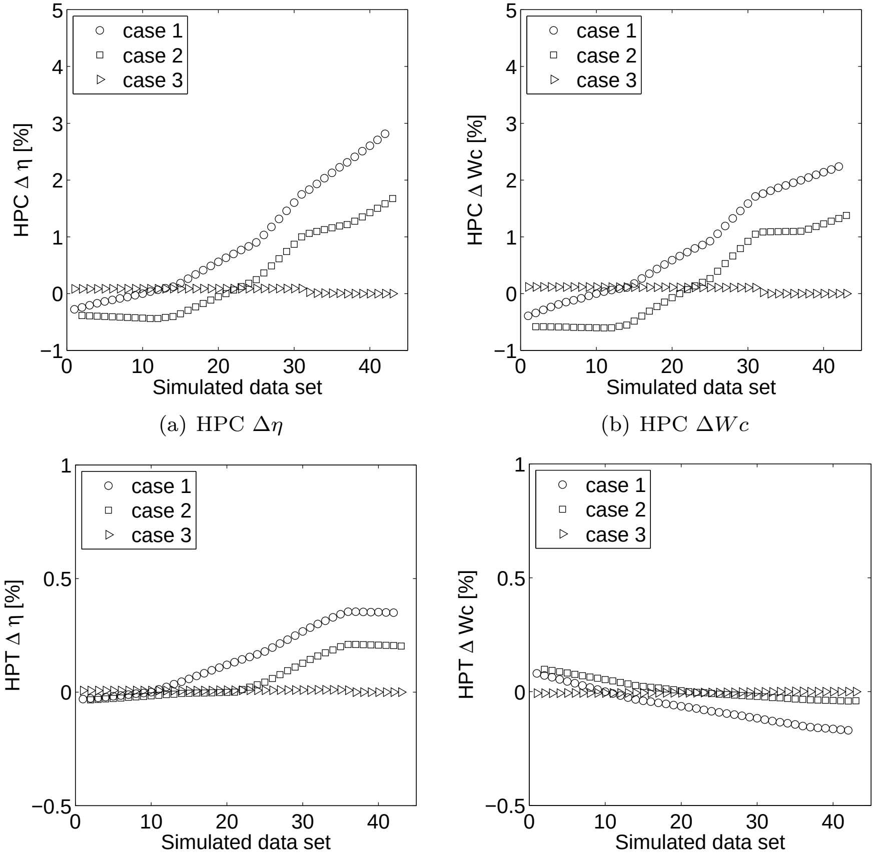
Off-design model calibration results

For cases 4, 5, and 6 the same reference data were used as for cases 1 to 3, but calibration was done using the off-design model calibration method. The corresponding calibration factors, presented in the last three data columns of table 4.4, indicate only minor variations between the reference data sets and the engine model. All calibration factors are close to 1.

The results, presented in figure 4.12, show the HPC and HPT efficiency and flow condition deviation trends superimposed on the results of cases 1, 2, and 3. While small differences are present in the results of cases 4, 5, and 6, they all correctly estimate zero component condition deviation for both components.

Although the results obtained with the off-design model calibration method all provide a reasonable match to the simulated condition, small errors remain. An example is the small shift observed in the HPC $\Delta\eta$ and ΔWc parameter trends around data point 30. These errors, which likely originate from rounding error in the numerical process, are at least an order of magnitude smaller than the condition deviations that are necessary for gas path diagnostics. Therefore, they are not investigated any further.

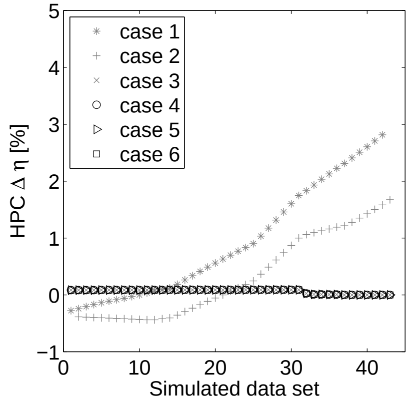
This model calibration study has demonstrated that model-based GPA that implements a design point model calibration method only functions correctly when the reference data are at the same power setting for which the model has been defined. When off-design reference data are used, calibration factors deviate from 1. This results in model errors that increase for power settings deviating from the calibrated power setting. This may lead to incorrect estimated condition deviations. With off-design model calibration, the AM calculation leads to the same results that were obtained through design point calibration using the design point reference data set. With that method, the operating point of the reference engine does not affect the GPA results.



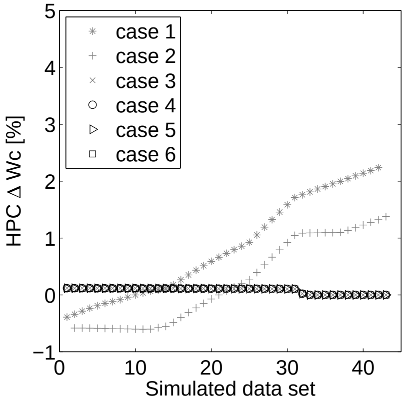
(a) HPC $\Delta\eta$ (b) HPC ΔWc

(c) HPT $\Delta\eta$ (d) HPT ΔWc

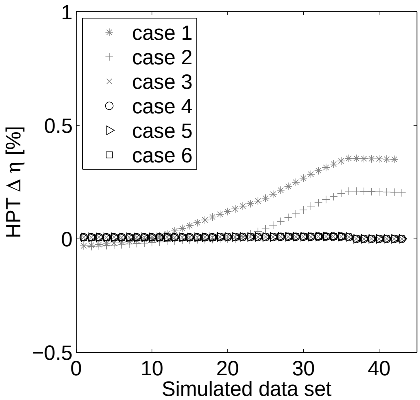
Figure 4.11: *The graphs show the GPA results of a single simulated data set containing no component deterioration that was analyzed using three different reference operating points. In cases 1 and 2 the performance model was calibrated with* off-design *reference data but the design point calibration method. Whereas the results of case 3 correctly indicate no condition deviations, the results from cases 1 and 2 incorrectly suggest condition deviations.*



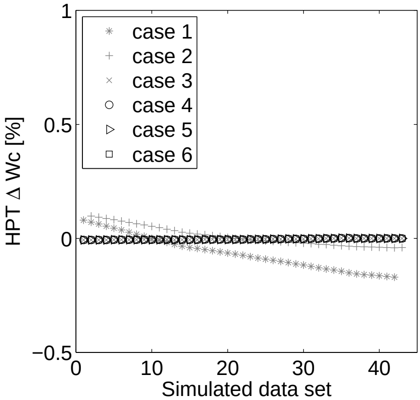
(a) HPC $\Delta\eta$



(b) HPC ΔWc



(c) HPT $\Delta\eta$



(d) HPT ΔWc

Figure 4.12: *The graphs show the GPA results of a single simulated data set containing no component deterioration that was analyzed using three different reference operating points. In cases 4 and 5 the performance model was calibrated with* off-design *reference data and the off-design calibration method. The GPA results that were obtained using the off-design calibration method all correctly estimate no condition deviation. Moreover, the estimated component condition deviations of the three cases overlap each other, suggesting a perfect agreement.*

4.4 Average reference data set definition

The off-design model calibration method presented in section 4.3 ensures model calibration when different reference performance data sets are used. Although this eliminates the model calibration error, the resulting component condition deviations are based on comparing a single measured data set to a single reference data set. When a poor reference data set is used for performance model calibration, GPA results may not reflect the correct condition deviation. This could potentially lead to incorrect maintenance actions.

Reference engines are engines with good overall condition and from which performance data are used for performance model calibration. A good reference engine for GPA applications is an engine for which the condition of all gas path components closely match design conditions. Engines with near-zero operating hours would be good reference engine candidates. Unfortunately, performance data from engines with near-zero operating hours and design condition for all gas path components are rarely available outside the engines OEM environment. In practice operational engines are used instead. However, this means that a potential reference engine may have clocked thousands of operational hours and may have been subjected to one or more maintenance cycles before its performance data are measured in a test facility.

A criterion for selecting good reference engines from a fleet of operational engines is the EGT margin. Engines with good overall performance have a high EGT margin. However, a high EGT margin is no guarantee that individual gas path components of an engine have a good condition. The EGT margin is a single metric resulting from the combined gas path component condition and interaction. A below-average condition of one component may be partially compensated by an above-average condition of another component. This effect is not captured by system-level engine condition indicators such as the EGT margin.

4.4.1 Condition variation among reference engines

Component condition deviations of engines with high EGT margins should exhibit minor variations. To study the variation among engines with relatively high EGT margins, the top ten engines of two CF6-80C2 thrust ratings were analyzed using the GSP AM component. The EGT margins of the selected engines are shown in table 4.5. The performance data set that was used for creating the baseline performance model also served as the reference data set for this study. Therefore, this data set closely matches the baseline performance model and the resulting model calibration factors are approximately 1.00.

Figure 4.13 shows the GPA results for both thrust ratings. Even though the high EGT margins are a measure of good overall performance, considerable variation is observed. While for some condition parameters the variation is

Table 4.5: *The top 10 exhaust gas temperature margins of the CF6-80C2A5 and CF6-80C2B1F engines available in the data base.*

EGT margin [K]	
CF6-80C2A5	CF6-80C2B1F
44	90
43	83
42	81
42	80
40	80
40	79
38	78
38	77
38	77
38	76

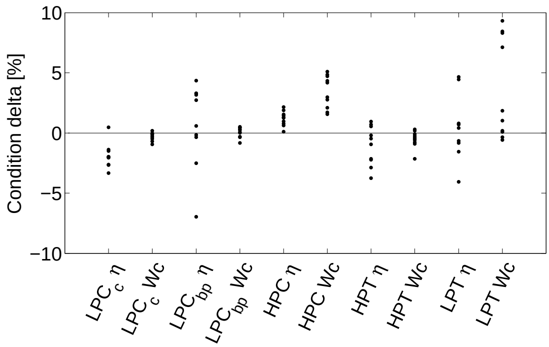
around 2%, other parameters vary more than 10%. This result suggests that the EGT margin criterion only may not be sufficient for selecting a good reference engine.

The observed variation is the combined effect of measurement uncertainty and engine-to-engine variation. Moreover, certain performance parameters are not measured, which may lead to extra component condition variation. The effects of measurement uncertainty were studied in section 4.1. The results of that study suggested that the variation of condition parameter deviations due to random measurement uncertainty is in the order of ±1%. Because some condition parameter variations observed in figure 4.13 are much more than ±1%, it is unlikely that random measurement uncertainty is the main cause of this variation.

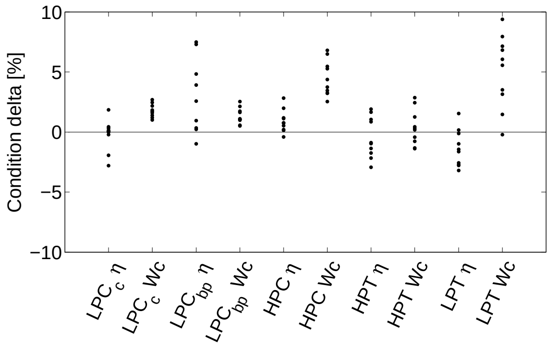
Effect of engine-to-engine variation

For gas path components that are restored to design condition during engine overhaul, variations within specified geometric tolerances may result in small engine-to-engine performance differences. These small variations may have observable effects on gas path component condition and their interaction during operation. However, in practice not all gas path components are restored to design condition during overhaul. Whether or not a component will be fully restored depends on the condition of that component as well as other factors such as financial and logistic factors. As a result, a larger condition variation is expected among recently overhauled engines with good overall performance.

The difference among engines with the top 10 EGT margins listed in table



(a) CF6-80C2A5



(b) CF6-80C2B1F

Figure 4.13: *GPA results obtained using the baseline reference data set.*

4.5 indicates that some variation in engine condition is likely. While this could be a reason for the variation observed in figure 4.13, some condition parameter deviations are much larger than the expected engine-to-engine variation among healthy engines. This means different mechanisms must be at work.

Effect of missing pressure and temperature measurements

Another possible cause of the observed variation could be that pressures and temperatures are not measured at all engine stations. While the data sets used for this study contained all measured performance parameters shown in figure 4.4, there were no measured data for the turbine inlet conditions(Tt4; Pt4), fan outlet temperature (Tt14), and low pressure turbine (LPT) outlet pressure (Pt5). Instead, fuel flow (W_f) and thrust (FN) are used to specify the thermodynamic cycle.

Apart from FN and W_f, additional estimated performance parameters are necessary for specifying the thermodynamic cycle. These are either constant values or variables that depend on off-design component performance described by component maps. Small errors in the component maps and assumed constants combined measurement uncertainty may lead to larger uncertainty in the cycle compared to direct pressure and temperature measurements.

Consider for instance the conditions at station 4: the HPT inlet. If the temperature and pressure would have been measured the uncertainty can be described by:

$$Tt4_{meas} = Tt4 \pm \delta_{Tt4} \tag{4.2}$$

$$Pt4_{meas} = Pt4 \pm \delta_{Pt4} \tag{4.3}$$

Because these parameters are not measured, they can be described by the following relations:

$$Tt4 = Tt3 + \frac{\eta_{cc} \cdot LHV \cdot W_f}{\dot{m}_a \cdot C_{pg}} \tag{4.4}$$

$$Pt4 = Pt3 - \Delta P_{cc} \tag{4.5}$$

Although the simplified combustion equation in equation 4.4 is not used in the performance model, it can be used for demonstrating the effect of uncertainty propagation and amplification. Including the uncertainties for the measured values in these relations while assuming that η_{cc}, LHV, C_{pg}, and ΔP_{cc} are known constant values results in:

$$Tt4_{est} \pm \delta_{Tt4} = (Tt3 \pm \delta_{Tt3}) + \frac{\eta_{cc} \cdot LHV \cdot (W_f \pm \delta_{W_f})}{(\dot{m}_a \pm \delta_{\dot{m}_a}) \cdot C_{pg}} \tag{4.6}$$

$$Pt4_{est} \pm \delta_{Pt4} = (Pt3 \pm \delta_{Pt3}) - \Delta P_{cc} \tag{4.7}$$

Rewriting these relations and neglecting the products of the relative uncertainties results in:

$$Tt4_{est} \pm \delta_{Tt4_{est}} = Tt3 + \frac{\eta_{cc} \cdot LHV \cdot W_f}{\dot{m}_a \cdot C_{pg}} \pm \delta_{Tt4_{est}} \tag{4.8}$$

$$Pt4_{est} \pm \delta_{Pt4_{est}} = Pt3 - \Delta P_{cc} \pm \delta_{Pt4_{est}} \tag{4.9}$$

where

$$\delta_{Tt4_{est}} \approx \delta_{Tt3} + \frac{\eta_{cc} \cdot LHV}{C_{pg}} \left(\frac{\delta_{W_f}}{|W_f|} + \frac{\delta_{\dot{m}_a}}{|\dot{m}_a|} \right) \tag{4.10}$$

and

$$\delta_{Pt4_{est}} = \delta_{Pt3} \tag{4.11}$$

Comparing δ_{Tt4} to $\delta_{Tt4_{est}}$ and assuming that Tt4 has a similar uncertainty as Tt3, it follows from equation 4.10 that $\delta_{Tt4_{est}} > \delta_{Tt4}$. On the other hand, assuming no error in the combustion chamber pressure loss factor ($\delta_{\Delta P_{cc}} \approx 0$) it follows that $\delta_{Pt4} \approx \delta_{Pt3}$. Thus, because Tt4 and Pt4 are not measured, the uncertainty associated with the calculated alternatives is larger. A similar derivation can be performed for Tt14 and Pt5. This effect is shown graphically for several parameters in the T-s diagram in figure 4.14.

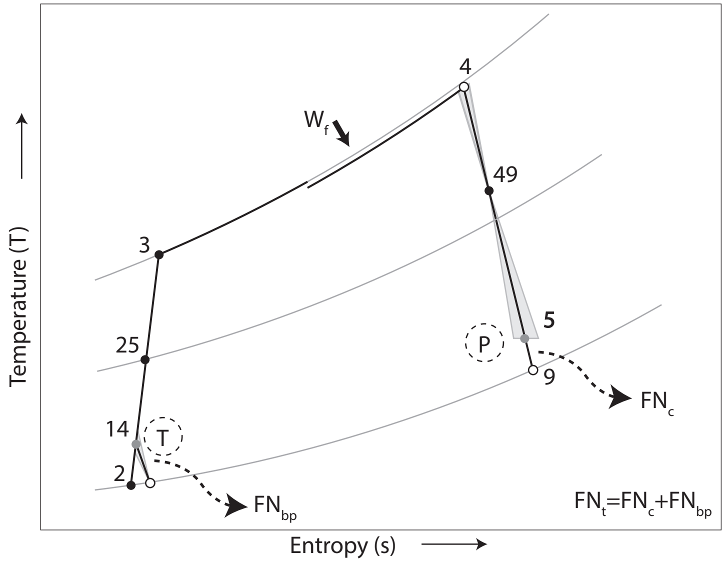


Figure 4.14: *Temperature-entropy diagram for a turbofan engine. Fuel flow (W_f) and (total) engine thrust (FN_t) are used for specifying the thermodynamic cycle instead of the missing pressures and temperatures: Tt14, Tt4, Pt4, and Pt5. Total engine thrust (FN_t) is the sum of the fan thrust (FN_{bp}) and core engine thrust (FN_c). This results in larger uncertainty for performance parameters that are not directly measured.*

For accurately estimating efficiency and flow capacity deviations of a gas path component, pressure and temperature data are necessary for the inlet and outlet of that component. When proxy parameters are used instead, the uncertainty of inlet and exit condition predictions may be larger than the measured values. This may be the cause of the relatively large variations of the $LPC_{bp}\,\Delta\eta$ and $LPT\,\Delta W_c$ values in figure 4.13 for engines with good overall performance suggested by their high EGT margins.

4.4.2 Using multiple reference engines

Because in practice the condition of reference engines is not known in detail and because the issues discussed in the previous section cannot be eliminated, a single reference data set may not be sufficient for reliably evaluating GPA results. An alternative approach is to use multiple reference engines for estimating the condition of a single engine. When n reference engines with good overall performance are used for GPA, the AM calculation is performed n times. The idea of this approach is that the average of those n sets of GPA results may provide a more reliable result than those obtained by means of a single reference data set.

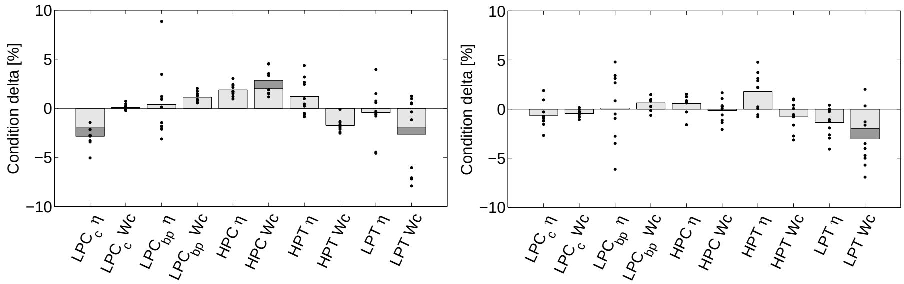
To analyze this concept, average condition deltas were calculated for two engines with relatively good EGT margins. Two engines of the same type but with different thrust ratings were selected for this study: one CF6-80C2A5 and one CF6-80C2B1F engine. The EGT margins of the selected engines are shown in table 4.6. Compared to the engines with highest EGT margins in table 4.5, this shows that both engines had relatively high EGT margins for their respective thrust rating, which should result in minor condition deviations. Ten reference engines of the corresponding thrust rating with good overall condition were used. As before, the EGT margin was used as selection criterion and the resulting top 10 engines for each thrust rating are shown in table 4.5.

Table 4.6: *EGT Margin of the CF6-80C2A5 and CF6-80C2B1F engines that are used for estimating an average condition deviation based on multiple reference engines.*

Thrust rating	EGT margin [K]
CF6-80C2A5	37
CF6-80C2B1F	74

The GPA results of this analysis are presented in figure 4.15. The markers indicate the condition delta variation for individual reference engines. The bar chart shows the average condition deviations. The variation observed relative to the average results can be considered an indication of the validity of the estimated average. For some condition parameters this variation is relatively small suggesting higher confidence for those parameters, while for other parameters it is large in relation to the average results.

In the previous section it was mentioned that the reliability of GPA results depends on measurement uncertainty effects, engine-to-engine differences, and the availability of performance parameters measurements. While none of those effects can be eliminated for operational engines, using multiple reference engines gives an indication of this inherent uncertainty. Adding the limits of the observed variation as confidence intervals is a useful method for judging the



(a) CF6-80C2A5 (b) CF6-80C2B1F

Figure 4.15: *GPA results obtained using multiple reference data sets of engines with good overall performance. The EGT margin was used as criterion for selecting reference engines.*

validity of GPA results when they are used in a maintenance process.

4.4.3 Average reference data set

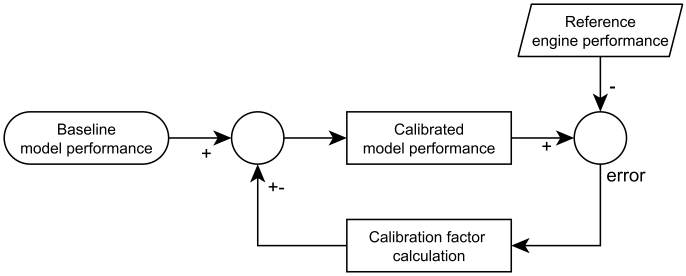
While averaging GPA results obtained from multiple references generates useful confidence intervals, it requires repeated adaptive modeling calculations followed by estimating the average and corresponding variation. Instead of using multiple reference engines, a single reference data set can be calculated that produces the same averaged condition deviations. This average reference data set represents the average performance of the reference engines used for calculating it. The confidence intervals obtained while creating this data set may be superimposed on the GPA results.

Figure 4.16 shows the two steps–model calibration and model adaptation– of the adaptive modeling calculation process. The difference between the baseline model performance and a reference engine performance is used for estimating the calibration factors, and the calibrated performance model is adapted such that it matches the measured data set.

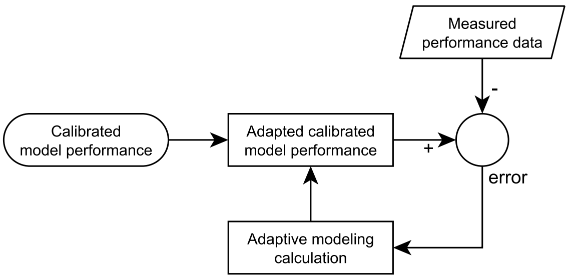
To determine an average reference data set and corresponding calibration factors based on the results of multiple reference engines the following steps are necessary:

1. Take the average GPA result for each condition parameter of an engine (Engine A) that are obtained from a series of AM sessions with different reference data sets.

2. Run a performance calculation with the baseline model at the same operating conditions as Engine A.



(a) Model calibration



(b) Model adaptation

Figure 4.16: *Figure (a) shows how calibration factors are used to eliminate the error between the baseline model performance and the reference engine performance to obtain a calibrated model. Figure (b) shows how the calibrated model is subsequently adapted such that the error between the adapted model and measured data are minimized.*

3. This is followed by a performance calculation with a deteriorated model at the same operating conditions as Engine A. The simulated deterioration is the averaged condition parameter deviation obtained from step 1.

4. Calculate the corresponding calibration factors by dividing each measured performance parameter from Engine A by the corresponding parameter of the deteriorated model:

$$f_{c_i} = \frac{P_{i(meas.)}}{P_{i(det.model)}}$$

5. Calculate the new reference data set by multiplying the calibration factors from step 4 with the the corresponding parameter of the baseline

performance model:

$$P_{i(ref.)} = f_{c_i} \cdot P_{i(base.model)}$$

.

4.4.4 Case study

To verify that the average reference data set generates the same GPA result as the result obtained with multiple reference engines, a case study is presented. Condition deviations for an CF6-80C1B1F engine with a relatively low EGT margin of 25 Kelvin are calculated two times. First with all the top 10 reference engines, and then with the average reference data set. The results of these calculations are presented in figure 4.17 and table 4.7.

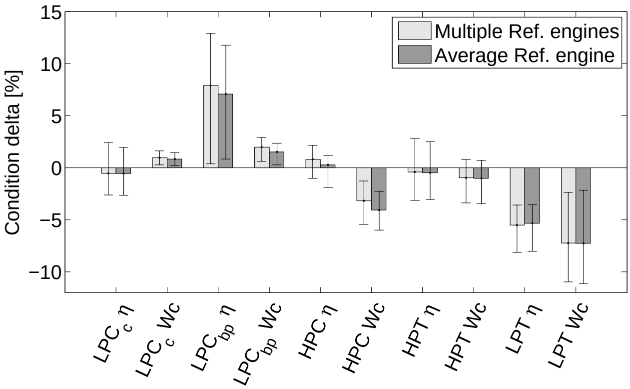


Figure 4.17: *Comparing GPA results obtained with the average reference data set to the results obtained with multiple reference engines.*

Figure 4.17 shows that the results obtained from both calculations are in agreement. Although there appear to be a small difference for some condition parameters, the differences are well within the confidence intervals. The confidence intervals for the analysis with multiple reference engines are based on the variation observed among the reference engines. For the results obtained with the average reference data set the confidence intervals are based on the variation observed while creating the reference data set. They are superimposed on the GPA results. Comparing the positive and negative errors in table 4.7 shows that the differences between calculated and estimated confidence intervals are relatively small.

This case study has shown that a single average reference data set that is obtained from multiple reference engines can be used for GPA instead of

Table 4.7: *Comparison of GPA results and confidence intervals obtained with the average reference data set to the averaged results obtained with multiple reference engines. ϵ^+ and ϵ^- are respectively the positive and negative error.*

	Avg. ref. data set			Multi. ref. engines		
Cond.Par.	Δ	ϵ^+	ϵ^-	$\bar{\Delta}$	ϵ^+	ϵ^-
LPCc η	-0.56	2.51	2.07	-0.53	2.95	2.08
LPCc Wc	0.84	0.60	0.63	0.96	0.68	0.68
LPCd η	7.07	4.69	6.23	7.92	4.99	7.54
LPCd Wc	1.53	0.84	1.26	1.97	0.94	1.35
HPC η	0.29	0.90	2.20	0.81	1.36	1.83
HPC Wc	-4.06	1.81	1.92	-3.16	1.89	2.27
HPT η	-0.47	2.99	2.58	-0.39	3.21	2.72
HPT Wc	-1.02	1.73	2.42	-0.96	1.79	2.42
LPT η	-5.33	1.79	2.69	-5.50	1.92	2.60
LPT Wc	-7.24	5.08	3.88	-7.23	4.87	3.71

multiple reference engines. In addition, the confidence intervals belonging to the average reference data set show good agreement with those calculated for this case study. This suggests that the pre-calculated confidence intervals are a good estimate for those based on multiple reference engines.

4.4.5 Different reference data sets for each thrust rating

Turbofan engines of the same type may be used for different aircraft types, each with its own thrust requirements. Instead of designing engines for each application, the engine control system enables this multi-aircraft flexibility by adjusting maximum take-off thrust accordingly. Table 4.8 shows the maximum take-off thrust for a few thrust ratings of the General Electric CF6-80C2 turbofan. Even though engines with different thrust ratings are geometrically identical, at maximum take-off thrust they operate at different operating points from a thermodynamic perspective.

Analysis has shown that errors may occur when GPA results for an engine are obtained with reference data of an engine with a different thrust rating. This effect, which is caused by off-design model inaccuracies, can be corrected by model calibration. Table 4.9 shows the calibration factors belonging to the average reference data sets that were derived in section 4.4.3. These reference data sets were based on a selection of engines with the best overall performance for the thrust rating. While the differences between the resulting calibration factors appear small, using calibration factors of a different thrust rating for

Table 4.8: *A short list of some CF6-80C2 thrust ratings and the corresponding maximum thrust at sea level conditions. Source: [16].*

Thrust rating	Max thrust [kN]
CF6-80C2A2	233.4
CF6-80C2B1F	254.3
CF6-80C2B6F	267.0
CF6-80C2A5	267.3
CF6-80C2D1F	270.0

GPA can magnify these errors. In worst case the errors are of the same order of magnitude as the performance deviations caused by component condition deterioration.

For example, consider a performance model calibrated for the CF6-80C2B1F thrust rating being used for analyzing a data set from an CF6-80C2A5 engine. The performance parameter deviations resulting from this 'incorrect' calibration can be estimated with equation 4.13. This is only an estimate because the difference in operating conditions affects these results. For an AM calculation these performance deviations are considered effects of component condition deterioration and result in non-zero condition deviations. The effect of this 'incorrect' calibration is shown in figure 4.18. Figure 4.18(a) shows the performance parameter deviation between the average reference data set of the A5 and the B1F engines. The resulting condition deviation with confidence intervals is shown in figure 4.18(b).

$$E_{P_{i(cal.model)}} \approx \frac{f_{c_i(B1F)} \cdot P_{i(base.model)} - f_{c_i(A5)} \cdot P_{i(base.model)}}{f_{c_i(A5)} \cdot P_{i(base.model)}} \tag{4.12}$$

$$E_{P_{i(cal.model)}} \approx \frac{f_{c_i(B1F)} - f_{c_i(A5)}}{f_{c_i(A5)}} \tag{4.13}$$

While calibration factors at one operating point cancel residual model errors, the differences in operating points between the two thrust ratings counteracts model calibration and amplifies existing model errors. Under these circumstances, the resulting condition deviations may originate from both model error and actual component deterioration. This would not occur if the performance model would be accurate over a wider operating range.

Unfortunately, the component map tuning method discussed in section 4.2 could not be applied to improve model accuracy. Despite the large volume of performance data for engines of several thrust ratings, only single data sets were available for each engine. Therefore, these results suggest that to minimize model-related error effect on GPA results, a reference data set is necessary for

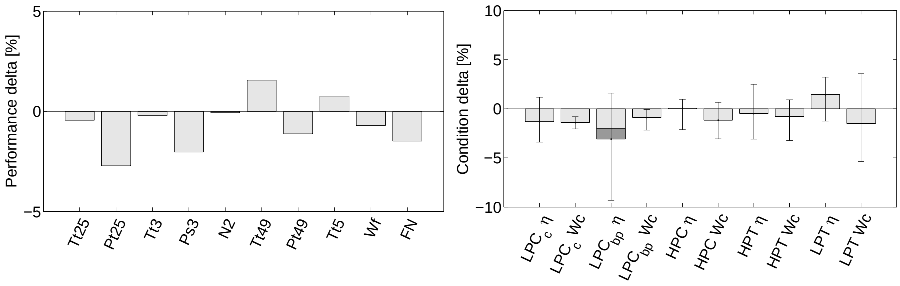
Table 4.9: *Model calibration factors belonging to the average reference data sets of the CF6-80C2A5 and CF6-80C2B1F thrust ratings. The calibration factors for Tt2, Pt2, RH, and N1 are 1.0, which indicates that simulated performance occurs at the same operating conditions as the reference data set. The remaining calibration factors cancel performance differences between the model and reference data.*

Parameter	CF6-80C2A5	CF6-80C2B1F
Tt2	1.0	1.0
Pt2	1.0	1.0
RH	1.0	1.0
N1	1.0	1.0
Tt25	0.998	1.002
Pt25	0.979	1.004
Tt3	1.001	1.002
Ps3	1.009	1.026
N2	1.001	1.003
Tt49	1.001	0.986
Pt49	0.981	0.991
Tt5	1.011	1.005
Wf	0.998	1.009
FN	0.992	1.011

each engine thrust rating that differs significantly with respect to other thrust ratings.

Multi-point calibration

An alternative solution to using separate reference data sets for each thrust rating would be using the concept of multi-point calibration [19, 62, 73] and use a single reference data set in combination with calibration functions. However, because it was shown that the condition of engines with good overall performance may exhibit significant variation, this would require several steps. The first step would be estimating the average condition for each thrust rating and defining average reference data sets that are based on those results. Subsequently, a functional dependency must be established for each calibration factor. This has the potential of introducing additional complexity as these functions can principally depend on several operating condition parameters, including inlet conditions, power setting, and installation effects such as power off-take and compressor bleeds [73]. Because the additional work and complexity were thought to outweigh the benefits, the choice was made not to pursue this path in this thesis.



(a) Performance deviation (b) Condition deviation

Figure 4.18: *Performance and condition deviation results obtained by performing an AM calculation where the condition of the average CF6-80C2A5 reference data set is compared to the average CF6-80C2B1F data set. It shows the effects of calibrating the performance model for a different thrust rating.*

4.5 Conclusion

Performance model accuracy, measurement uncertainty, and the availability of performance measurements along the gas path can greatly affect the reliability of GPA results. In addition, the results are highly dependent on the fitness of the reference data used for GPA. While in theory some errors may be reduced to less significant levels, in practice this is not feasible outside the engine OEM environment. Without detailed design information from engine manufacturers, improving model accuracy by using performance data from operational engines can be done up to a certain level. The objective of the work discussed in this chapter was improving reliability of GPA results and quantifying important error sources.

- Installing additional sensors in the gas path for better condition monitoring and gas path diagnostics is not possible for operational turbofan engines. At best, known error sources can be quantified and included in the GPA results. It was demonstrated that the effects of measurement uncertainty can result in relatively wide confidence intervals for some condition parameter deviations. Particularly when proxy parameters are used as an alternative for unavailable pressure or temperature measurements in the gas path.
- Component maps that were tuned using a combination of adaptive modeling and on-wing measured performance data improved model accuracy at off-design operating points necessary for on-wing GPA. With this approach component maps available from the public domain were adapted

with more detail than just scaling relative to a reference point. The tuned compressor maps provided more realistic correlations between the corrected mass flow and the shaft speed. This method improved the accuracy of gas path analysis with on-wing measured performance data.

- The remaining scatter of flow capacity was not the result of customer bleed. When customer bleed flows are active while measuring engine performance parameters but their effect is not taken into consideration when using these performance data for GPA, the results may indicate non-existent component condition deviations. Under those circumstances, GPA results should not be trusted.

- Incorrect model calibration may lead to significant errors. With the off-design model calibration method any off-design operating point can be used as reference data set.

- Although the methods presented in this chapter helped reducing model errors, effects of measurement uncertainty remained. Effects of random sensor errors are relatively small compared to errors originating from incorrect model calibration and missing gas path pressure and temperature measurements.

- When considering the challenges discussed in this chapter a useful approach is to base GPA results on multiple reference data sets. While this may be achieved by means of separate GPA runs for each reference data set and calculation of an average result, defining an average reference data set is a more time-efficient way of achieving this goal. Especially when this approach is applied in the aero-engine maintenance process. Defining an average reference data set based on multiple reference engines with good overall performance was demonstrated as an effective approach. Basing GPA results on multiple reference data sets allows visualization of otherwise unknown uncertainty in condition parameters and provides a way for judging the validity of the results.

CHAPTER 5

Expanding gas path analysis benefits for maintenance

Abstract

Gas path analysis (GPA) is widely applied on engine test rig data to isolate components responsible for performance problems, thereby offering substantial cost-saving potential. Additional benefits for the aero-engine maintenance may be obtained by systematically using GPA for analysis of performance data measured during both test cell and on-wing operation. This chapter synthesizes the work discussed in chapters 3 and 4 and presents the experience with model-based GPA on large volumes of measured performance data obtained from the operational environment. Case studies demonstrate some of the benefits for the aero-engine maintenance process.

The content of this chapter is based on:

Verbist, M.L., Visser, W.P.J., and van Buijtenen, J.P., **Experience with gas path analysis for on-wing turbofan condition monitoring.** Journal of Engineering for Gas Turbines and Power 136(1), GTP-13-1212 (Oct 25, 2013)

The GSP adaptive modeling component has been used for gas path analysis of several different gas turbine engine configurations [4, 11, 45, 50, 52, 54, 64, 69, 76]. Because it enables estimating gas path component condition from a performance perspective, GPA can help to determine necessary maintenance actions for restoring poor engine performance. This information also helps preventing unnecessary engine disassembly and part replacements. This way, GPA may offer substantial cost-savings for gas turbine maintenance.

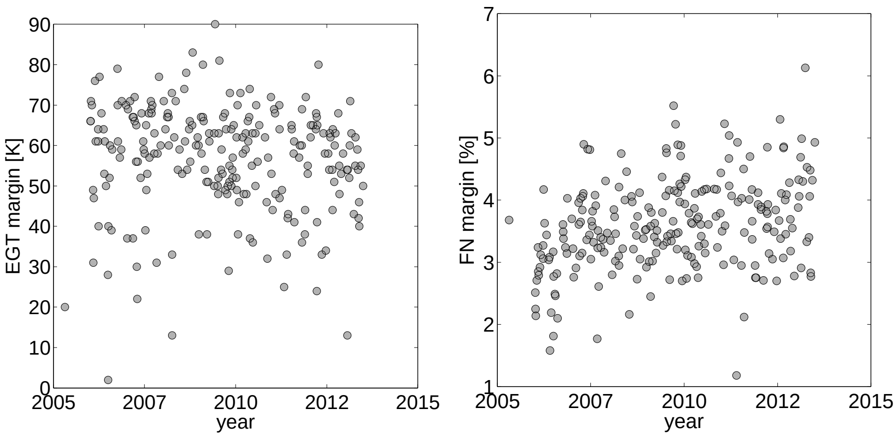
Most studies that demonstrated the GPA capability of the GSP AM component were focused on individual engine cases. The scope of those studies was limited because the objectives were proof of concept studies for a particular engine type or demonstrating GPA benefits to a gas turbine MRO. However, there were other reasons that limited the scope of these studies also. In some cases engine design and performance data that are necessary for GPA were not readily available and good baseline performance was not defined. In other cases, insufficient performance parameters were available for practical GPA application. In almost all cases performance data necessary for GPA were measured after maintenance. As a result, much time was spent on finding the necessary data for GPA and when results were obtained they were of limited use for the maintenance process of the engines in question.

To benefit from GPA in the maintenance process, the results should be reliable and GPA need to be used systematically. Although GPA results are most valuable for individual engines prior to maintenance, the additional costs of pre-overhaul (or inbound) performance tests limits this approach. Chapter 3 has demonstrated that on-wing measured performance data may be a good alternative to these in-bound performance tests. By combining the GPA accuracy improvements presented in chapter 4 with the information system concept presented in chapter 6 additional benefits can be realized. These benefits are not limited to individual engine cases, but also apply to the maintenance process in general. This chapter includes a few case studies for demonstrating the benefits of systematically using GPA in the maintenance process.

5.1 Additional benefits from test cell performance data

During post-overhaul performance testing several gas path performance parameters are measured and used for verifying that engine performance requirements are met. The objective is to identify engines with poor overall performance. Because operating conditions affect engine performance, measured performance parameters are corrected for those effects and for known losses. The resulting corrected performance parameters then are affected by engine condition and power setting only.

However, despite these parameter corrections there are no unique signatures for specific gas path component condition deterioration. Therefore, corrected performance parameters are used to create parameter groups that provide more information about the engine as a system. Examples are specific fuel consumption (SFC), exhaust gas temperature (EGT), and corrected thrust (FNK). The engine OEM specifies the maximum permissible limits for these performance parameter groups. The difference between the system parameter values and the corrected value at specific operating conditions is defined as the performance margin. These performance margins provide valuable information about the overall engine condition.



(a) (b)

Figure 5.1: *EGT margin and thrust margin trends for a fleet of CF6-80C2B1F engines.*

Trending performance margins is useful for monitoring engine performance as well as for monitoring maintenance effectiveness. It allows identifying engines with deviating performance relative to an engine fleet average. In addition, parameter trends are useful for observing long-term engine-related performance changes such as aging of a fleet, or performance changes resulting from gradual test facility performance drifting. Figure 5.1 shows two examples of EGT margin and thrust margin trends over time. Despite the useful information on engine fleet condition, they provide limited information about the root cause of an observed trend.

5.1.1 Correlating system parameters to component condition

Performance margins would be more informative if they could be related to component condition. More specifically, if correlations between performance margins and component condition deviations can be observed they may help identifying specific components responsible for low performance margins. This information can be valuable for verifying the effectiveness of the maintenance process. For example, if an engine has a low EGT margin and poor HPT condition, and there exists a positive correlation between EGT margin and HPT condition, the best course of action for performance restoration could be additional repairs of the HPT.

EGT margin

Two important performance margins are the EGT margin and the SFC margin. The EGT margin is a measure of overall engine condition. As gas path component condition deteriorates, more fuel is necessary for generating the same thrust. For a constant thrust setting, this leads to temperature increases in the turbines and a reduction of the EGT margin. Therefore, a low EGT margin is an indication of poor overall engine condition. Gas turbine MROs often guarantee minimum post-overhaul EGT margins as part of a maintenance agreement with the engine owner or operator. Occasionally post-overhaul EGT margins are lower than expected. When this occurs additional repairs are necessary or financial penalties are paid by the gas turbine MRO.

Figure 5.2 component condition deviations as function of the hot day EGT margin for approximately 200 CF6-80C1B1F engines. The performance data of these engines were measured during their post-overhaul performance acceptance test. To obtain the best possible GPA result, only data sets were selected that included an LPT out temperature (Tt_5). Component conditions deviations for each data set were calculated with GSP's AM component. An average reference data set was used for the AM calculation. This average reference data set was defined using the ten engines with the best overall condition according to their EGT margin. Chapter 4.4 describes the method for defining an average reference data set by means of multiple reference engine data sets. The EGT margins are calculated from observed performance parameters with equations and correction factors specified by the engine OEM.

Several interesting phenomena can be seen in the scatter plots in figure 5.2. First, strong correlations are observed between the EGT margin and both HPC condition parameters. These correlations stand out in comparison to the condition parameter deviation trends in the other scatter plots. The strong correlations suggest that the EGT margin is more sensitive to the condition of the HPC than other gas path components. In addition, the gradient of

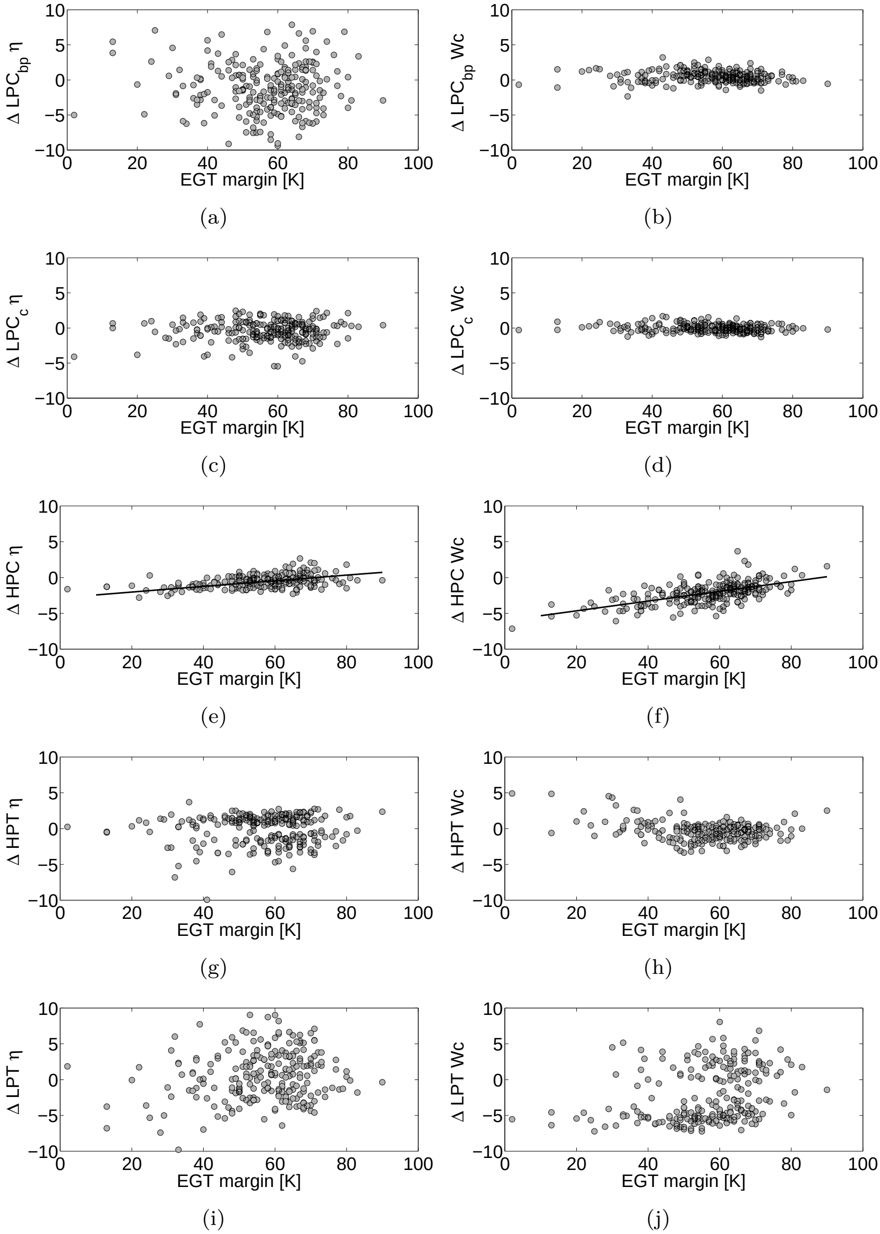


Figure 5.2: *Component condition parameter trends as function of EGT margin. Each scatter plot contains data of approximately 200 CF6-80C2B1F engines.*

the linear line passing through the points for the HPC flow capacity is larger for the HPC flow capacity deviation than for the HPC efficiency deviation. This suggest that the HPC flow capacity is slightly more important than the efficiency. However, in practice this difference is not very useful as there is no way of independently affecting individual condition parameters of a gas path component.

Two other observations in figure 5.2 are the large scatter for some condition parameters, and *clustered distributions* for the LPT flow capacity and HPT efficiency. Chapter 4.4 demonstrated that the absence of direct pressure and temperature measurements in the gas path is the likely cause of the large scatter. In figure 5.2(g) and figure 5.2(j) the data points in the scatter plots appear to be clustered in two groups. While this clustered distribution could be the result of different maintenance work scopes, similar results are not seen for the other condition parameter of the HPT and LPT. If the maintenance work scope caused this clustering, both condition parameters of a gas path component are expected to exhibit a similar distribution.

Alternatively, the clustering may also be the result of multiple solutions for the numerical problem in combination with the relative high uncertainty of some condition parameters due to missing performance parameters. Because Tt_{14} and Pt_5 are not measured, there may be multiple solutions for the fan bypass efficiency and LPT flow capacity deltas, which cause the relative large scatter.

Because the largest step in performance restoration, in terms of EGT margin gain, can be obtained from overhauling core engine components—the HPC and HPT—low pressure components such as the fan, booster, and LPT often receive minimal to no maintenance. However, that choice depends on their condition and the remaining life of life limited parts. Due to the uncertainty associated with the estimated LPT flow capacity, this clustered distribution can also be observed for the HPT efficiency. Because of the scatter and the clustered distribution, correlations between those condition parameters and the EGT margin are not visible.

SFC margin

The other important performance margin, the SFC margin, is a measure of overall fuel efficiency. A low SFC margin is a sign of poor engine performance. Fuel efficient engines are important from both an environmental as well as a financial point of view. While complete engine overhaul would likely result in good fuel efficiency, the corresponding maintenance costs would be very high. Knowing which components are responsible for poor fuel efficiency of a specific engine is the first step in determining the necessary maintenance actions to ensure efficient engine performance at acceptable maintenance costs.

Figure 5.3 shows scatter plots of the component condition deviations as

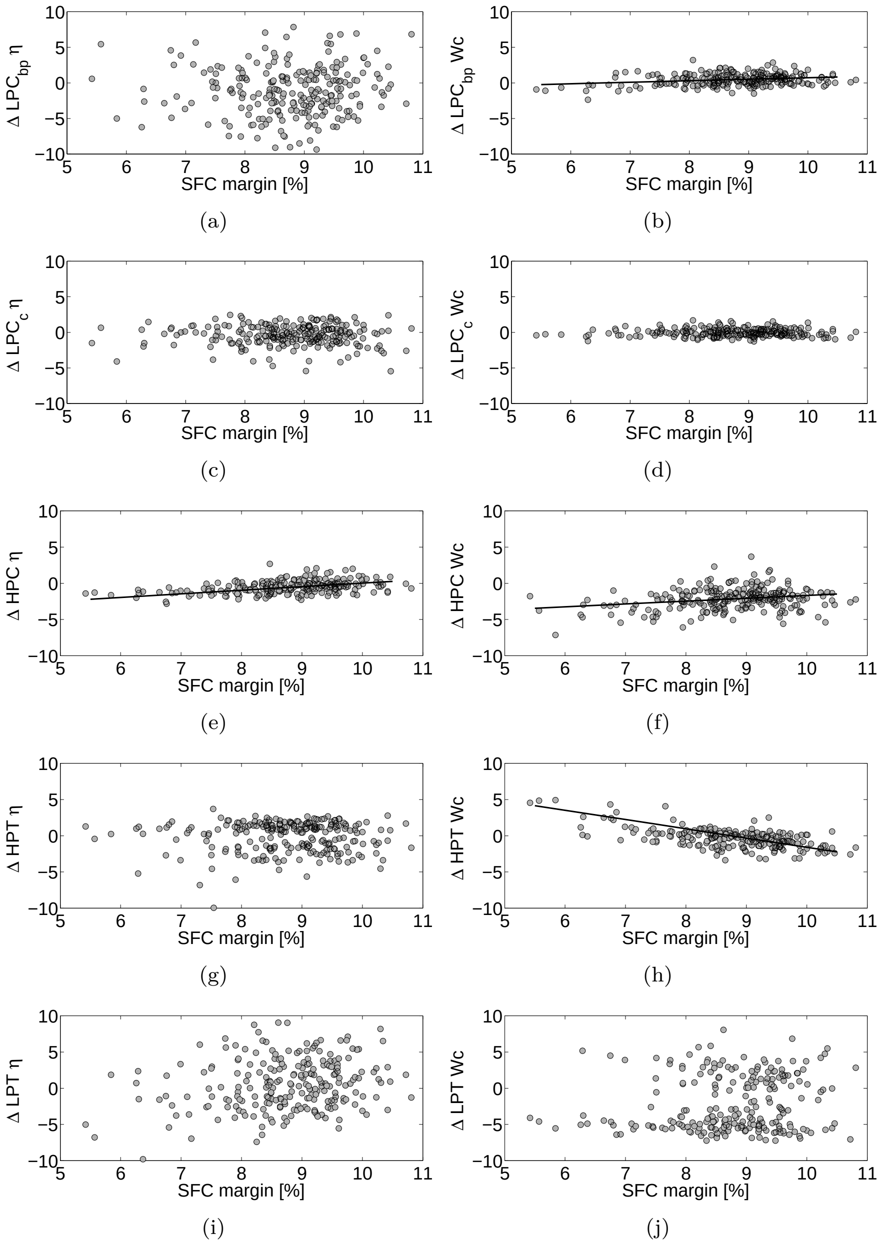


Figure 5.3: *Component condition parameter trends as function of SFC margin. The scatter plots contain data of approximately 200 CF6-80C2B1F engines.*

function of the SFC margin for approximately 200 CF6-80C1B1F engines. As with the EGT margin trends, the SFC margins are calculated from observed performance parameters with equations and correction factors specified by the engine OEM also. Even though some similarities are observed between figures 5.2 and 5.3, different correlations emerge from the scatter plots.

The fan bypass flow capacity delta and the HPC efficiency delta have a slightly positive correlation with the SFC margin. But the most notable correlation is observed between the HPT flow capacity and the SFC margin. This correlation suggests that a low HPT flow capacity is beneficial for overall fuel efficiency. While this cannot be realized without affecting other condition parameters, it does show the importance of this condition parameter for overall fuel efficiency.

The HPT flow capacity is mainly dictated by shape and cross-sectional area of the high pressure nozzle guide vanes (NGVs) located at the combustor exit. The total NGV cross-section area is an important parameter that is carefully measured and documented upon engine re-assembly. Several NGV sections together form the NGV component. The sections are selected such that the overall NGV area is within the margins specified by the OEM. The NGV component receives the hot gas flow from the combustor and its function is to turn and accelerate the gas flow to meet the first stage of the HPT rotor blades. If the speed and angle with which the accelerated gas flow meet the HPT rotor blades are not in perfect agreement along the radial direction of the rotor blades, the energy conversion process becomes less efficient. For a given temperature drop across the turbine less energy can be extracted for driving the compressor. While the interaction leading to a power balance between the HPC and HPT is quite complex, in essence it means that more fuel would be necessary to for extracting the required energy. Therefore, the knowledge that the NGV area also has a relatively strong effect on the SFC may help decide how to select the individual NGV sections from a fuel efficiency standpoint in addition to the OEM specifications.

Other parameter correlations

The examples used in this section gave a brief demonstration of the useful information that can be obtained when GPA is used systematically for analyzing post-overhaul performance data. A similar approach can be used for searching other useful correlations between performance margins and component condition parameters.

A database that contains relevant data is an important aspect for effectively implementing such a capability. Apart from measured performance data and GPA results, the database used for this study also contained calculated performance margins. If other data such as information about maintenance work scopes or engine geometry are also systematically stored, other parameter correlations may be discovered that can help improve the maintenance effectiveness.

5.2 On-wing component condition monitoring using GPA

Reliable turbofan operation is critical for successful airline operation. During on-wing operation, performance parameters such as exhaust gas temperature (EGT) margin are monitored and used as an indicator for overall engine condition. Gas path component deterioration leads to component performance degradation, which normally results in a reduced EGT margin. With GPA, individual gas path component performance degradation can be determined, providing a much more detailed indication of the engine condition and root cause of EGT margin reduction. This offers a significant potential to enhance safety, reliability, availability and the maintenance process. At the post-overhaul performance test, GPA helps to isolate the root cause of performance problems, saving costs by avoiding unnecessary disassembly and part replacement.

Using steady-state performance data obtained from engines equipped with all available sensors provides the best opportunity to assess engine condition. Ideally, GPA is applied before overhaul, offering assessment of individual component condition and an effective method to determine the required work scope for each gas path component to ensure sufficient EGT margin after engine overhaul. Unfortunately, because of the additional cost associated with inbound test runs these are rarely conducted. However, with GPA applied to on-wing measured performance data, the objective of component condition assessment prior to overhaul can also be realized.

This section describes the application of model-based GPA on large volumes of on-wing measured performance data. Background information is given about the GPA tool used and issues with using on-wing measured performance data for GPA are discussed. Two cases studies are used to demonstrate GPA with on-wing data monitoring component condition and detecting sudden component condition changes and sensor problems.

5.2.1 GPA with on-wing measured performance data

For the study described in this section, on-wing measured performance data of a CF6-80C2 fleet are used. These engines are equipped with an extended condition monitoring sensor package. As a result, the same performance parameters are measured along the gas path during both test cell and on-wing operation. The approximate sensor locations are shown in the schematic of a turbofan in figure 5.4. During on-wing operation relative humidity and engine thrust are not measured. If direct thrust measurements are not available, fan bypass static outlet pressure (Ps_{14}) is a good proxy to represent engine thrust [71]. Because relative humidity was not measured during on-wing operation, dry air conditions are assumed for the analysis of on-wing performance data. Because the actual relative humidity will differ, the effect will manifest itself as an uncertainty of the GPA results [43]. However, the effects of relative humidity variation on sea level take-off performance are relatively small and were therefore ignored.

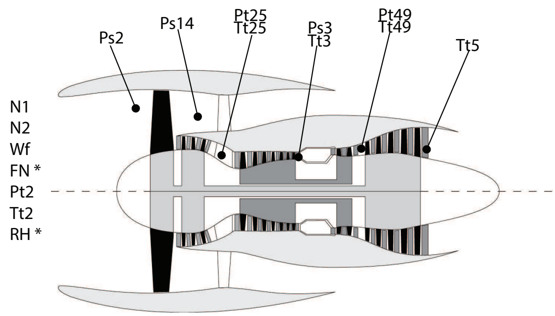


Figure 5.4: *Sensor locations in the GE CF6-80C2 turbofan engine. * Parameters that are not measured during on-wing operation.*

In real-life scenarios operating conditions may vary considerably between consecutive performance snapshots. In addition, performance degradation occurs simultaneously in all components but at different rates. These variations all affect engine performance and the accuracy of GPA results. Accurate GPA is challenging when performance data are affected by variable operating conditions and measurement uncertainty. Consequently, the results of GPA with on-wing measured performance data contain significant scatter. All these effects make GPA with on-wing measured performance data more challenging than GPA with data measured in a controlled test cell environment.

Table 5.1: *Maximum permissible customer bleed flow mass fraction at steady state take-off power.*

Bleed location	Mass fraction
Stage 8	8.8 %
Stage 14	5.0 %

On-wing installation effects

Apart from variable operating conditions, on-wing engine performance is affected by several types of installation effects. Customer bleed flows cause the most significant installation effect since they can account for a significant fraction of compressor airflow. Table 5.1 shows the maximum permissible bleed flow fractions during take-off. Depending on the engine power setting, customer bleed is extracted from the 8^{th} or the 14^{th} high pressure compressor stage. However, during performance testing the customer bleed flow ducts are closed. Since the performance models used for GPA were based on test cell performance data, customer bleed flow effects were not taken into account. Due to bleed flow extraction the state of the gas at the compressor exit is different. When the models are used for GPA with on-wing data, these bleed flows should be taken into account. To demonstrate the effect of neglecting active bleed flows, a simple experiment was conducted. A performance model was created that included bleed flows. This model was used for generating several performance parameter sets for different levels of bleed flow. These were subsequently analyzed with an identical model apart from the bleed flows. Figure 5.5 shows the effect on GPA results when active bleed flows are not taken into account. Increased customer bleed leads to increased condition deviations for all components. These results show that neglecting active customer bleed can lead to incorrect GPA results. However, during the critical take-off operating condition, customer bleed usually is minimal. But since bleed flows are not measured, this could not be verified directly.

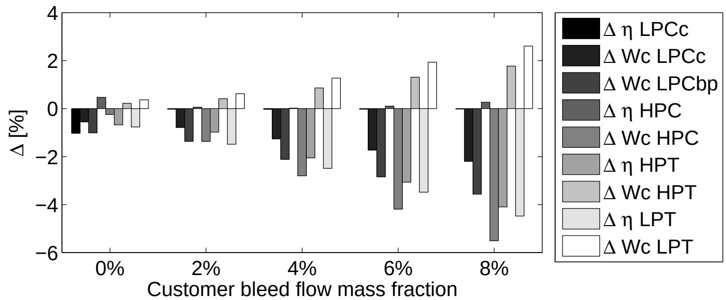


Figure 5.5: *Effects of increasing customer bleed flow on GPA results when these are not taken into account in the model.*

A second installation effect originates from different inlet and exhaust nozzles. During a performance acceptance test a turbofan is equipped with a different inlet nacelle and sometimes also with different exhaust nozzles. In a test cell, bell mouth inlets are used for optimal inlet airflow with minimal losses. However, during on-wing operation the inlet airflow can be distorted by many factors. Ensuring stable engine inlet flow while also maintaining the capability to handle large inlet angles of attack requires specially designed inlets. These have sizes and efficiencies different than their test cell counterparts. Similar to customer bleed flows, not taking these effects into account may compromise GPA results.

A third installation effect is resulting from the mechanical power taken from one of the engine shafts to drive accessories such as generators and fuel and oil pumps. On the test rig, power off-take ('PTO') by accessory components is minimal, but on-wing, electric power off-take is unknown. However, compared to the total power delivered by the turbines, the accessories consume a relatively small fraction of the power; total PTO is typically ≈300 hp (≈0.4% of the HPT power delivered during take-off). These effects on GPA results can therefore be neglected. Because the PTO is not measured, a constant value is assumed.

And finally a significant effect may also be caused by variations in shunt factors. In turbofan engines, sensors are connected to the engine control unit (ECU). The ECU converts the sensor input signal to a parameter value that can be read by an observer such as the cockpit crew. To provide a consistent parameter value with different engines types on the same aircraft for example, factors can be imposed on the actual sensor readings. Shunt factors may be different for test cell and for on-wing operation. The effects can be eliminated by using a reference data set from the same source (i.e. on-wing reference for on-wing GPA, and test-bed reference for test-bed GPA). This is a must if the shunt factors are unknown.

Measurement uncertainty

Measurement/sensor error may significantly affect GPA results. This is because GPA is based on analysis of small deviations (usually <10%) in performance parameters values. Consequently, the effect of measurement error on the deviations is large. For most sensors used, uncertainty information can be derived from general guidelines and be used for an overall GPA uncertainty analysis.

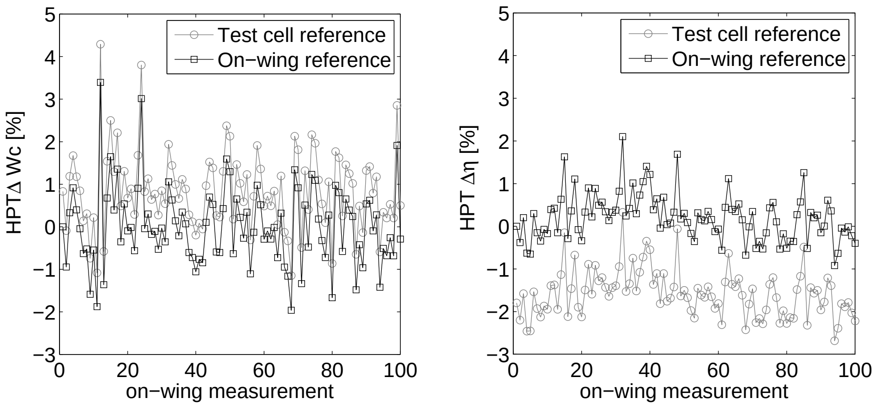
A source of GPA uncertainty comes from variable operating conditions during take-off. Whereas steady state performance is confirmed during engine performance testing before measurements are recorded, this is not possible during on-wing take-off performance. During take-off, inlet conditions change and full steady state operation is never achieved when the performance snap shot is taken. This is another source of measurement uncertainty that affects the GPA results with on-wing performance data.

The distribution of the errors and deviations affecting GPA uncertainty mentioned in the previous sections is mostly unknown. Therefore, according to Taylor[63] the combined effect of these uncertainties can be assumed to have a Gaussian distribution. This assumption is important for the statistical analysis of the GPA results.

Reference engine for on-wing GPA

The goal of GPA with on-wing measured data is identification and quantification of component condition parameter changes over an extended period. This requires an initial reference condition from which to measure change. As mentioned earlier, reference engine performance data are necessary for the AM calculation. For on-wing GPA there are two options for choosing a reference engine.

The first option is using test cell performance data measured during the most recent post-overhaul acceptance test. This seems a logical choice because the controlled operating conditions during engine testing ensure accurate performance data. However, because of installation and shunt factor effects, the same engine operating on-wing may well generate notably different measured performance data. Consequently, using the most recent test cell performance data as reference for GPA with on-wing data will result in condition deviations starting from the first take-off. This effect is shown in figure 5.6 for the HPT efficiency and flow capacity deviations.



(a) Flow capacity deviation (b) Efficiency deviation

Figure 5.6: *The effect of using reference data measured in a test cell or on-wing. Although the trends of the estimated HPT component condition deviations are very similar for both reference data sets, the offset observed when using test cell reference data incorrectly suggests a deteriorated component.*

The second option is using the first on-wing measured data set after overhaul as reference. Because both reference engine data and the subsequent on-wing performance data points contain the same installation and shunt factor effects, those effects on the GPA results are minimal. Moreover, the model calibration step of the AM calculation compensates for unknown installation effects. As a result, the estimated condition deviations show a similar amount of scatter, but initially centered on a zero mean. Consequently, using the first on-wing snapshot as reference for GPA with on-wing data produces a better initial estimation and allows for easier identification of long term condition changes (see 'on-wing reference' trends in figure 5.6(a) and figure 5.6(b)).

Statistical analysis

Because measurement uncertainty, variable operating conditions, and component deterioration affect on-wing turbofan performance, measured performance parameters show significant scatter. Consequently GPA results obtained from on-wing performance data also show significant scatter making the task to draw the right conclusions, isolating the major component condition deviations difficult.

Condition deviations caused by gradual deterioration mechanisms can be isolated from higher frequency fluctuations caused by measurement uncertainty and variable operating conditions (varying with each take-off). An exponentially weighted moving average (EWMA) was used to filter these higher frequency fluctuations and expose the lower frequency component condition deterioration. An EWMA assigns exponentially decreasing weights as observations get older. The EWMA is defined by equations 5.1 and 5.2, where x_i is the current observation; A_i and A_{i-1} are respectively the current and previous smoothed value. The coefficient α is the smoothing constant that has a value between 0 and 1.

$$A_i = \alpha \cdot x_i + (1 - \alpha)A_{i-1} \tag{5.1}$$

$$A_1 = x_1 \tag{5.2}$$

For smoothing the component condition deviation trends a value for alpha was chosen such that the residual errors between the smoothed and the observed value have a zero mean and approach a normally distributed probability density function. Figure 5.7 shows an example of the EWMA trend line where $\alpha = 0.135$. The probability density function of the residual errors for the smoothed trend is shown in figure 5.8. The PDF has a zero mean ($\bar{x} = -0.103$) and a standard deviation of 3.5 ($\sigma = 3.525$). With this information, the uncertainty of an observed deviation can be determined for each component condition parameter.

5.2.2 Case study: component condition monitoring

The first case study shows the additional information that can be obtained when GPA is used for on-wing component condition monitoring. While operating on-wing, performance monitoring techniques are used for trending pa-

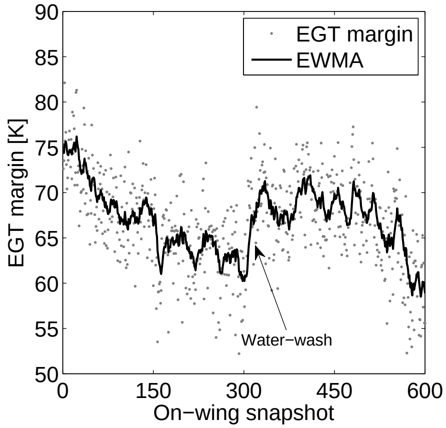


Figure 5.7: *Hot day exhaust gas temperature margin trend from approximately 600 sequential take-off snapshots.*

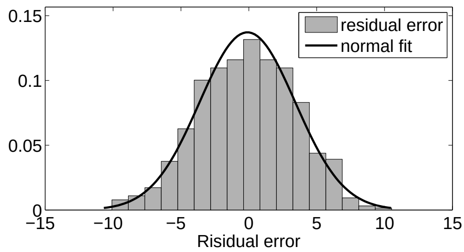
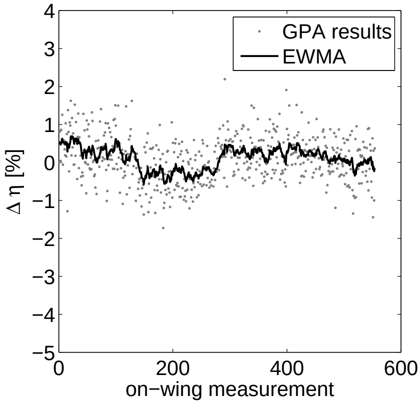


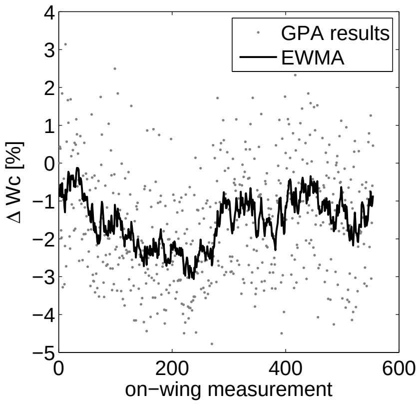
Figure 5.8: *Probability density function of the residual errors between the smoothed and observed value.*

rameters such as the exhaust gas temperature (EGT) margin and specific fuel consumption (SFC) margin. Figure 5.7 shows an example of an EGT hot day (HD) margin trend for an engine with a steady deterioration rate. Parameters like this only provide system level engine condition information. Although the gradual EGT hot day margin reduction observed during the first 300 take-off indicates engine deterioration, the root cause cannot be identified this way. After a small upward shift, the EGT margin is again gradually consumed. The small upward EGT margin shift indicated by the arrow in figure 5.7 is typically the effect of water washing.

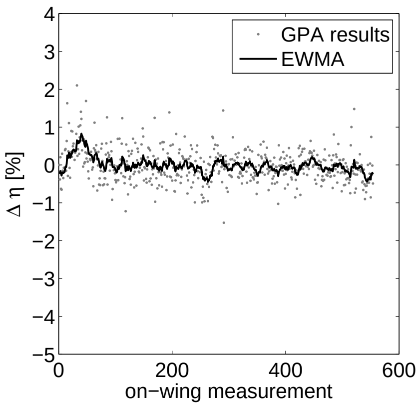
Results from GPA with the on-wing measured performance parameters are shown in figure 5.9. The shift observed in the EGT margin trend, which was attributed to the effect of water washing, was also observed in the HPC $\Delta\eta$ trend in figure 5.9(a). These results suggest that HPC efficiency loss can be



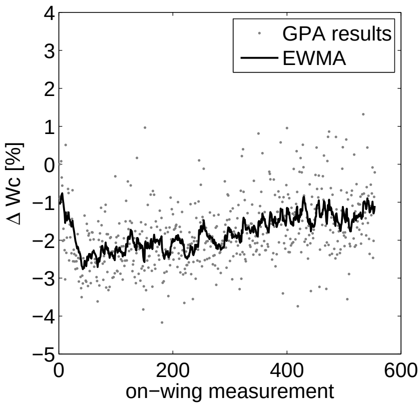
(a) $HPC\Delta\eta$



(b) $HPC\Delta Wc$



(c) $HPT\Delta\eta$



(d) $LPT\Delta Wc$

Figure 5.9: *HPC (figures a and b) and HPT (figure c) and LPT (figure d) component condition trends. An exponential weighted moving average (EWMA) is used to for smoothing the observed trend.*

partially recovered by water washing.

The water wash effect is not visible in the $\Delta\eta$ trend of the HPT or the ΔWc trend of the LPT. These condition parameter trends suggest a slow but steady rate of component condition deterioration. The higher rates of the component condition changes observed in figure 5.9(c) and figure 5.9(d) for the first 30 take-offs is also typical for a recently overhauled turbofan engine. After overhaul, there is a so-called *run-in period* during which seals, shrouds and other newly fitted parts show a short period of rapid change after which they settle on a low rate of deterioration. This case study shows that GPA applied to on-wing measured performance data is able to identify the dominant component condition change due to water washing that leads to EGT margin gain, which is the HPC efficiency.

5.2.3 Case study: effects of sudden parameter shifts

For the second case study GPA is applied to on-wing measured data of an engine that experienced two sudden EGT margin shifts. Figure 5.10 shows a scatter plot of the EGT HD margin for a period of approximately 500 take-offs. This graph shows the two shifts marked by the arrows: a relatively small increase around the 130^{th} take-off, and a large drop around the 380^{th} take-off.

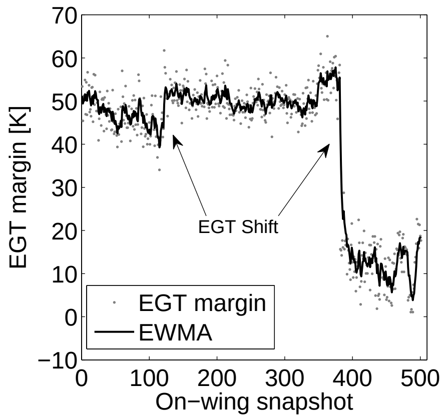


Figure 5.10: *Hot day exhaust gas temperature margin trend from approximately 500 consecutive take-off snapshots. The arrows indicate the observed EGT hot day margin shifts.*

Handling sensor errors

Similarly to the previous case study, the first EGT margin shift could be the effect of a water wash. However, closer inspection of the measured performance data around the time of the first EGT HD shift revealed a systematic sensor error. Figure 5.11 shows some of the observed temperatures and pressures along the gas path that have been corrected for inlet conditions, and the corrected shaft speeds for the same period as the EGT HD margin trend. A significant shift was observed for Pt_{25}, the booster outlet total pressure, around the same time as the first EGT shift. If sudden component deterioration would cause such a pronounced change of Pt_{25}, the effect should be visible in other parameters also. However, no other parameter showed any shift during the time frame of the first EGT margin shift. Therefore, we concluded that the observed Pt_{25} shift resulted from a faulty sensor.

The sudden downward shift of the pressure sensor suggests some sort of blockage. Because this happened around the small upward EGT margin shift, which could be the result from water washing; it is possible that the sensor got blocked during the water wash. Unfortunately, no information about that event was available to verify this hypothesis.

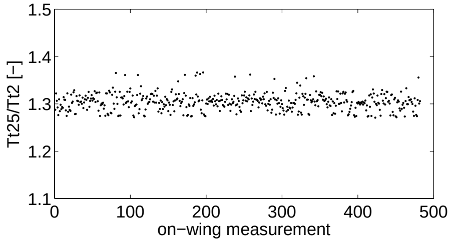
Because of the significantly lower Pt_{25}sensor reading, the AM calculation could not converge. The pressure was too low to achieve a thermodynamically feasible operating point. This converge problem indicated that the Pt_{25} pressure reading was conflicting with the engine cycle thermodynamics (in terms of conservation of energy).

Although the Pt_{25} trend in figure 5.11(d) shows a significant change, it does not directly indicate sensor failure. Moreover, it also contained certain features (peak values) that were observed in the parameter trends for Tt_{25}/Tt_2 and Ps_3/Pt_2. We attempted to compensate the suspected Pt_{25} error by adding a constant offset value to the sensor reading.

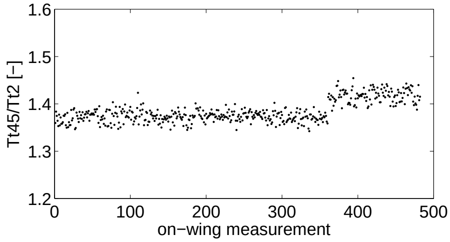
To determine the constant offset value we first corrected the observed Pt_{25} values for ambient temperature and pressure. Linear trend lines were created for the data before and after the shift. The offset value was estimated such that the trend lines matched where the Pt_{25} shift occurred. Figure 5.12 shows the original Pt_{25} parameter data and the data with the offset value. With an offset corrected Pt_{25} sensor, the AM calculation converged while using the on-wing performance data measured after the shift.

The second EGT HD margin shift, which occurred around the 380^{th} take-off, was also accompanied by a sudden Tt_5 shift. The sudden shifts that were observed in multiple measured parameters suggested a change of engine condition. Because of the large decrease of Tt_5, which was in the order of 200 Kelvin, GSP could not converge to a valid (measurement adapted) operating point. Unlike the Pt_{25} shift, the large Tt_5 shift showed a rapid change in a short time span. Because the observed large downward shift seemed unlikely, especially when the corrected Tt_{45} temperature remained constant, it was an indication that the Tt5 sensor malfunctioned.

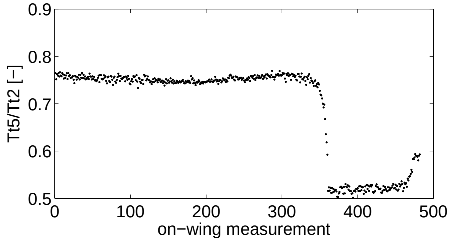
Convergence of GPA applied to the on-wing measured data after the large



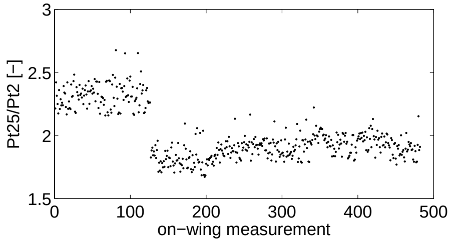
(a) Corrected Tt25 temperature trend.



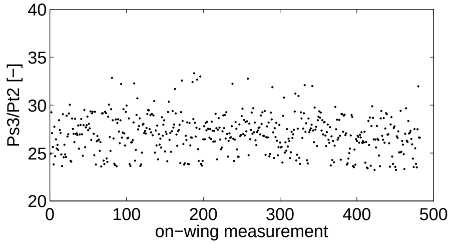
(b) Corrected Tt45 temperature trend.



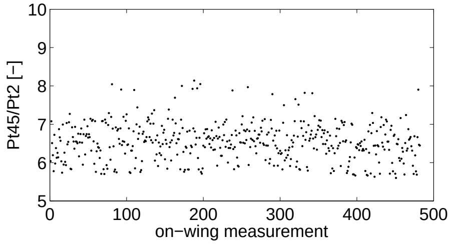
(c) Corrected Tt5 temperature trend.



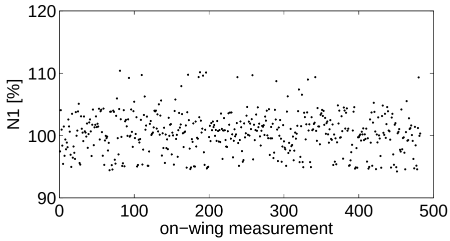
(d) Corrected Pt25 pressure trend.



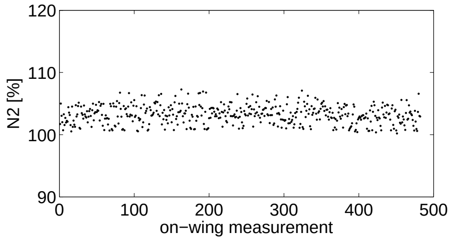
(e) Corrected Ps3 pressure trend.



(f) Corrected Pt45 pressure trend.



(g) Corrected N1 trend.



(h) Corrected N2 trend.

Figure 5.11: *Corrected performance parameter trends.*

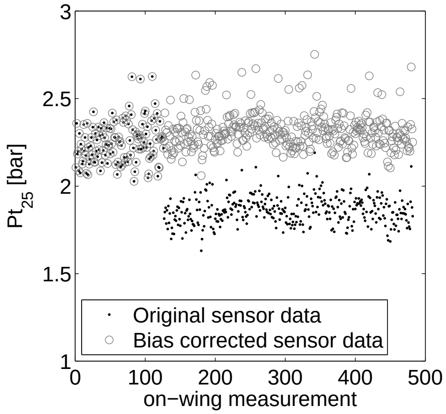


Figure 5.12: *This figure shows the original Pt_{25} parameter data including the downward shift, and the data corrected with the offset value.*

EGT HD margin drop was only possible by disregarding the Tt_5 sensor data. To account for one less measured parameter, the LPC_{bp} $\Delta\eta$ condition parameter was also removed from the analysis [74]. Because of the modifications necessary for dealing with this on-wing measured performance data set, analysis was done in three intervals:

- Interval 1: take-off 1 to take-off 129: GPA with all available data up to the Pt_{25} sensor shift.
- Interval 2: take-off 130 to take-off 380: GPA with an offset value to compensate for the P_{25} shift.
- Interval 3: take-off 381 onward: GPA with the Pt_{25} off-set but without Tt_5 and LPC_{bp} $\Delta\eta$.

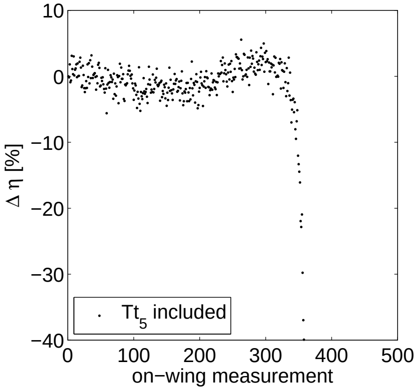
Results and discussion

For this analysis, the first on-wing data set was used as reference. The GPA results are shown in figures 5.13 and 5.14. The results of GPA applied to the on-wing data of interval 1 showed approximately constant condition deviations with scatter of a few percent for most components. GPA results from data of the second interval indicated condition deviations for the compressors, but almost no change for the turbines. The increase observed for both condition parameters of the HPC could be the result of water washing. But, because an offset value was added to the faulty Pt_{25} measurement, the estimated condition deviations could also result from using an incorrect offset value. However, when comparing the GPA results for the HPC to the results of the previous case study, similar characteristics emerge. Both compressors display a positive increase of isentropic efficiency deviation which is followed by a slow decrease over time. The ΔWc condition trend shows the same behavior. The difference between both cases is the amount of observed scatter in the GPA results. The increased levels of scatter for this case could have resulted from the larger uncertainty related to the constant offset value that was used.

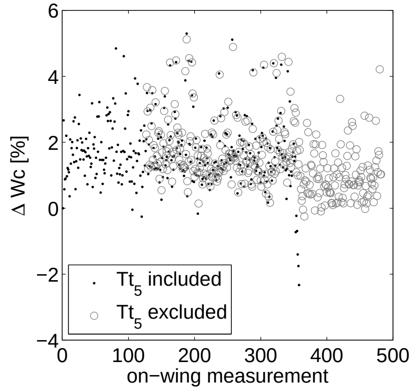
Analyzing the performance data from the third interval required excluding the Tt_5 sensor. To verify that excluding this sensor would result in similar condition estimations compared to when $Tt_5$was included, analysis of the second interval was performed two times; one time with Tt_5 included and one time without Tt_5. The gray markers in figures 5.13 and 5.14 show the GPA results obtained without the Tt_5sensor. The close match observed for most condition parameters confirmed that without the Tt_5 sensor almost the exact same condition deviations result from the AM calculation.

However, there were some exceptions. The most noticeable difference was observed in figure 5.13(e) for the LPT $\Delta\eta$ around the 350^{th} take-off snapshot. Although the ΔWc of the combined fan core and booster and fan bypass also showed small differences between GPA results with and without the Tt_5 sensor for the same interval, the estimated LPT $\Delta\eta$ went beyond normal values. The LPC bypass $\Delta\eta$ in figure 5.13(a) exhibited the same extreme behavior. The GPA results for these condition parameters showed good agreement for approximately 200 take-offs after the first EGT margin shift, but started to deviate near the 350^{th} take-off. Because this deviation started before the second EGT margin shift, it is likely that those were the first signs of component deterioration. Although GPA could not isolate the actual root cause immediately, it appeared to capture early signs of a developing problem before this resulted in a shift of the EGT HD margin. Upon closer inspection of the EGT HD margin around the 350^{th} take-off in figure 5.10, a short upward trend is visible that could be the early indication of a problem. However, increased EGT margins generally suggest an improvement of overall engine condition which could result from on-wing maintenance actions such as engine water washing. An increased EGT margin does not suggest engine deterioration and will normally not set off condition monitoring alerts.

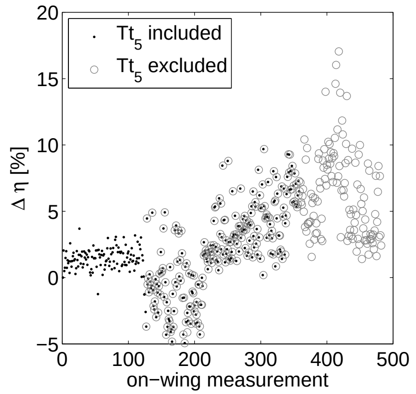
GPA results of the on-wing data from the third interval indicated sudden condition changes for several components. The HPT showed a sudden decrease of a few percent in both the efficiency and flow capacity condition parameters, whereas the LPT only has a sudden decrease of flow capacity ΔWc. However, normal turbine deterioration generally manifests itself as an increase of ΔWc. Due to erosion, corrosion, and blade rubs, the effective turbine flow cross-area increases which results in an increased flow capacity. An example of this can be seen in figure 5.9(d). The sudden ΔWc decrease observed for both components suggest a different component deterioration mechanism.



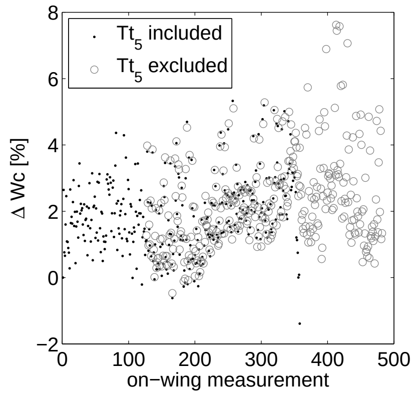
(a) $LPC_{bp}\Delta\eta$



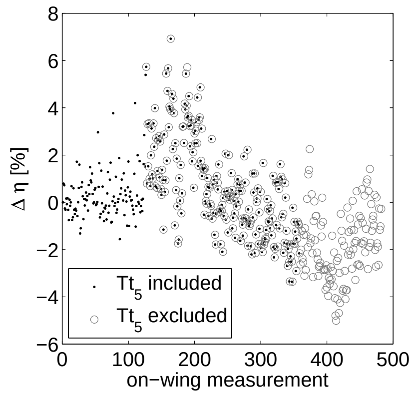
(b) $LPC_{bp}\Delta Wc$



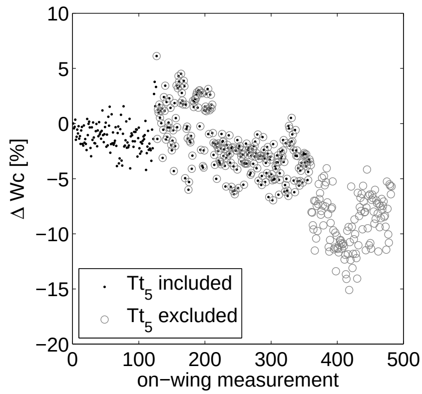
(c) $LPC_c\Delta\eta$



(d) $LPC_c\Delta Wc$

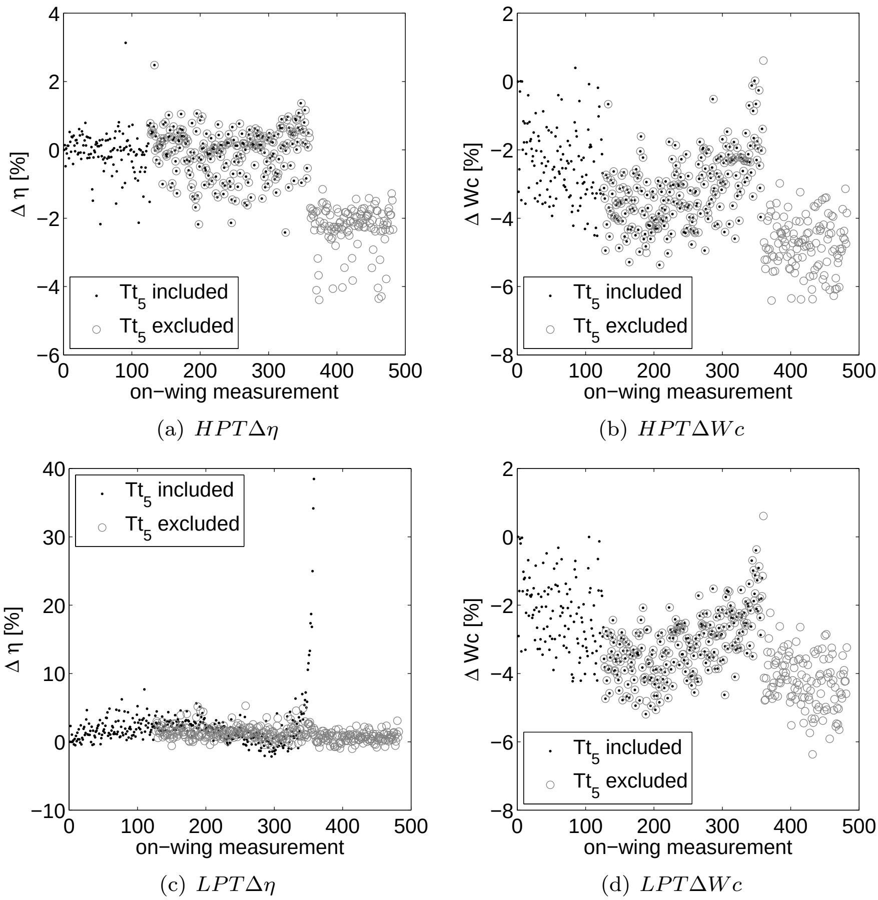


(e) $HPC\Delta\eta$



(f) $HPC\Delta Wc$

Figure 5.13: *Estimated efficiency deviation trends (figures a, c, e) and flow capacity deviation trends (figures b, d, f) for the fan bypass, the combined fan core and booster, and the high pressure compressor.*



(a) $HPT \Delta\eta$ (b) $HPT \Delta Wc$

(c) $LPT \Delta\eta$ (d) $LPT \Delta Wc$

Figure 5.14: *Estimated efficiency deviation (left) and flow capacity deviation (right) for the HPT and LPT.*

Visual inspection after engine removal revealed that the engine suffered from combustor damage. A large section of the combustor liner was broken off, most likely in small increments, which damaged both the HPT and LPT as the combustor liner pieces exited the engine through the exhaust nozzle. The observed damage to the turbine blades, which was more severe for the HPT, explained the reduced flow capacity that was observed for both components.

This case study demonstrates the ability of on-wing GPA analysis to isolate the root cause of sudden EGT margin shifts. For this particular case, GPA was also able to identify a problem before this was visible in the EGT HD margin. Moreover, sensor error can be identified by manually manipulating suspect measured data, based on observed shifts in the trend.

5.3 Conclusion

The benefits of GPA for gas turbine diagnostics have been demonstrated extensively. However, GPA accuracy and reliability issues and the lack of systematic application limited the demonstration of potential benefits for the maintenance process. This chapter demonstrated some GPA benefits for the maintenance process by presenting a few case studies. It combined the GPA accuracy improvements presented in chapter 4 with the information system concept presented in chapter 6. Based on the results presented in this chapter the following conclusions were made.

- Apart from diagnosing engine condition from a performance perspective, GPA may offer substantial benefits for the maintenance process. One way of extracting useful information is by correlating performance margins to component condition. This approach enables establishing the relative importance of particular components on specific performance margins and may affect the maintenance work scope definition. This way, systematically using GPA for analyzing post-overhaul performance data provides useful information for the maintenance process.

- Even though variable operating conditions and measurement uncertainty affect the results of gas path analysis with on-wing performance data, the GSP AM component is capable of estimating component condition from on-wing measured engine data with sufficient accuracy for detailed condition monitoring. Because individual component condition parameter trends can be monitored while engines are installed on-wing, GPA with on-wing measured performance data has the potential for enhancing safety and providing valuable information for the maintenance process prior to engine removal. However, for reliable GPA results with on-wing measured performance data, sufficient performance parameters must be measured.

- GSP on-wing gas path analysis is an effective method for diagnosing engine problems and component failures before their effects become severe enough for detection by shifts in EGT margin trends.
- Sensor error can be identified by manually manipulating suspect measured data, based on observed shifts in the measured performance parameter trend. This process can be automated if added to the adaptive modeling calculation as an unknown fault variable.

CHAPTER 6

Information system concept

Abstract

GPA has been demonstrated as an effective tool for estimating gas path component condition. However, effectively integrating GPA into an aero-engine maintenance process requires a dedicated information system: a system that enables the interaction between people, processes, data, and analysis tools. An important element of an information system is the database. This chapter presents a relational database concept for GPA applications.

A GPA tool uses measured performance data to estimate gas path component condition deviations. That information helps to identify the root cause of poor engine performance. While the value of GPA for estimating individual engine condition has been demonstrated, this method provides additional benefits to the maintenance process when GPA is used systematically and the results are combined with other maintenance-related data. Moreover, when GPA is used for on-wing condition monitoring, engine condition can be monitored with much more detail compared to performance parameter trending methods. In other words, when data measured at several locations in the aero-engine maintenance and operational processes are analyzed and combined, the resulting information provides added value for the aero-engine maintenance process. To systematically use GPA and connect data from various locations in the aero-engine maintenance and operational processes an *information system* is essential.

An information system may be described as a system that enables interaction between people, procedures and technologies for collecting, storing and processing data. Its objective is to store data for processing into useful information and knowledge that can be used to support the control, planning and management processes in organizations. Most organizations or business enterprises use computer-based information systems for enabling the necessary information flows, but person-to-person interaction is also part of an information system.

In the aero-engine maintenance, repair, and overhaul (MRO) industry, information systems fulfill an important role. Safety and reliability considerations of aero-engines require that every step of the design, manufacturing, and maintenance process must be well documented. During the operational life of an aero-engine, all design modifications, remaining life, maintenance inspection results and many other aspects are continuously tracked to ensure safe and reliable operation. The information system facilitates the information flows to ensure that the aero-engine maintenance and operational processes run smoothly.

6.1 Data storage for effective GPA

The embedded generic adaptive modeling (AM) functionality of GSP that is used for GPA is being developed by Delft University of Technology since 2003. An graphical user interface was created for demonstrating the capabilities of the GSP GPA tool at KLM Engine Services [3, 4, 11, 18, 50, 64, 69]. The GPA tool enables rapid performance data import from the test facility into the AM component. While GPA results provide valuable information for individual cases of poor engine performance, they were not systematically stored or accessible for post-processing or future use. This aspect limited the added value of GPA for the maintenance process.

6.1.1 Text files for data storage

A data import routine for text files was implemented in the AM component. This routine has been developed with a high degree of flexibility and was well suited for proof-of-concept and demonstrating purposes. However, it required individual performance data files of a particular text file format. Table 6.1 shows a conceptual view of the performance data in text (ASCII) file format that is used for test cell performance reporting at KLM. A text file does not refer to a standard, a technology or a language, it is just a general concept that describes a style of data storage that is being used since the early development of the modern computer. It has no automatic linking with other pieces of information. Even though the format is solely designed for printing purposes, it is often used for storing data records sequentially in an ad hoc format.

Parameter name	Power setting #1	Power setting #2	Power setting #3
par 1	value	value	value
par 2	value	value	value
par 3	value	value	value

Table 6.1: *Example data structure used for demonstrating the GPA application.*

Advantages of using text files to store data are simplicity and the relatively little storage space it requires. However, using individual text files for performance data storage has some drawbacks that limit systematic application of GPA. First, retrieving a desired data set requires a custom method for locating the data. A commonly used method is to use a logical file and folder naming convention. For instance, test result file names may contain the time and date during which the test was executed, and files may be stored in separate folders for each engine type. While this method may help to find a test result file belonging to a particular test of an engine, it does not provide a mechanism to find data using search criteria other that date and engine type.

Another drawback is that a single text file with the format shown in table 6.1 contains only a single performance data set of a specific power setting. Although it can be extended to include multiple data sets for one power setting by using different names in the column headers, this has its limits and is not efficient when many data sets are available for an engine.

There is no mechanism that enforces constant and unique parameter names. As performance data files may contain more information than only gas path performance parameters, parameter names may be used several times in one file. For printing purposes this is no problem. However, ensuring that the correct parameter values are located in a text file with duplicate or similar parameter names requires additional coding of rules and exceptions that may become rather complicated and error-prone.

Finally, text files have no mechanism to hold any relations between the data tables included within them. This is an important limitation of using text files for storing data for which the time of measurement and the object it belongs to are essential. The absence of a mechanism to hold relations is the main drawback of using text files and limits systematic use of GPA in the aero-engine maintenance process at KLM.

6.1.2 Database storage

An alternative to storing data in text files is using a database. A database may be defined as a logically structured collection of relational data that is designed to effectively store, manage and retrieve the data. It is the central element of an information system. The idea behind using a database is that a user (or application) is not bothered with the physical data storage but only with the logical characteristics of the data. Physical data storage is managed by a *database management system* (DBMS); a software program that provides the interface between users (or applications) and a database as well as ensuring that a database remains a consistent state. The DBMS also controls data redundancy resulting is less data duplication and saving data storage space.

The data in a database are updated (inserted, modified, or deleted) and retrieved by means of *queries*. These are instructions presented to the database in a predefined format. Many database management systems use the Structured Query Language (SQL) for updating and retrieving data from the database. The following shows an example of a simple query that retrieves all records from two columns (column-1 and column-2) of table-1 where the value of column-1 must match CF6-80C2.

```
SELECT column-1,column-2
FROM table-1 WHERE column-1 = 'CF6-80C2';
```

In a similar way more complex queries can be set up for retrieving data from multiple tables while satisfying several criteria. A powerful advantage of using a database and SQL is that data cross-sections can be made. Cross-sectional data refer to observations of many different individuals (engines) at a given time, each observation belonging to a different individual. For example, a query can be set up to retrieve measured performance data from all engines for which only the core components were overhauled and failed the post-overhaul acceptance test. The data may then be used for GPA to see if there is a connection between certain component condition deviations and poor post-overhaul engine performance. This way, using cross-sectional data for GPA may generate knowledge that may be valuable for the maintenance process.

Because data are stored in a single location with a fixed logical structure and because data may be combined to create useful data cross-sections, using a database instead of text files is beneficial for systematically using GPA. GPA results may also be added to the database for further analysis. When connected to a database, the only information necessary for performing AM calculations is a specific data set. This way a database becomes an integral element of the AM component and enhances the generic functionality of the GSP GPA tool. However, performance data from multiple sources in the aero-engine maintenance and operational processes are not stored in the database automatically. While custom routines remain necessary for importing relevant data in a database, this task is managed outside the AM component.

6.2 Relational database model

The GPA database was created using the *relational database model* [6]. Formally, a relational database is a collection of related *entities*. Entities are the logical things or objects for which available data are stored in the database, e.g., engines, employees, books, etc. Entities are characterized by their *attributes*. These are the characteristics that are used for describing an entity such as, for instance, engine type, engine model, and engine serial number to describe an engine entity. Each description of an entity that contains values for its attributes is called an *instance* of that entity. An instance of an entity is uniquely identified by the value of its *primary key*; an selected attribute that is not allowed to have duplicate values.

From a user's perspective a relational database is a collection of related *tables* that store information about one or more entities. The *fields* (or columns) of the tables contain the attributes that characterize the entities in the table. Each instance of an entity is stored in a *record* (or row) of the table and contains a unique primary key value. Figure 6.1 shows the database features that have just been described. Although the remainder of this chapter will mainly use the more familiar terms: tables, fields, and records, the formal definitions are necessary for describing the principles of the relational database model.

In a relational database the relationship is a link between two tables that share one or more attributes. Consider for example the engine table in figure 6.1 that is related to a table containing information about performance test sessions. Possible relationships between tables are: one-to-one (1-1), one-to-many (1-∞), and many-to-many (∞-∞). Because an engine is likely to undergo several test sessions during its lifetime, the relation ship between the engine entity and the test session entity will be a one-to-many relationship. Figure 6.2

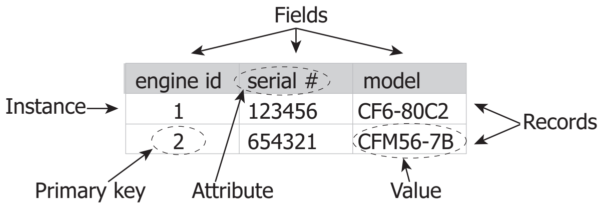


Figure 6.1: *This database table example shows some characteristic features of a relational database table.*

shows the entity-relationship diagram of the engine entity and the test session entity. One engine instance may be related 0, 1 or many test session instances. However, one test session instance must be related to one and only one engine instance. This aspect, which is called *referential integrity*, is a fundamental rule of the relational database model that must never be violated.

6.2.1 Database normalization

Database entities and corresponding attributes may be grouped and related to each other in more than one way. However, incorrectly grouping related entities (in different tables) may cause conflicts during database manipulation. While most conflicts can be prevented by using common sense during the database design process, some are more difficult to identify.

Normalization theory is a formal description of certain commonsense principles used for database design. It is used to effectively group the entities and attributes into groups and relations that prevent data manipulation problems [5, 21]. The theoretical rules that the design of the database relations meet are called *normal forms*, each of which represents an increasingly stringent set of rules.

When database relations are placed in the third normal form (3NF), most common problems related to bad relational designs may be avoided [21]. Discussing the various normal forms in-depth is beyond the scope of this thesis. However, because the relations of the GPA database concept are at least in 3NF, the first three normal forms shown in the following list are briefly discussed.

The first normal form states that *all data are stored in two-dimensional*

Figure 6.2: *A one-to-many relation between the engine entity and the test session entity.*

tables with no repeating groups. A repeating group is a field for which more than one value in each record of the table may exist. Consider for example, the Engine table. It may contain fields describing the engine serial number (ESN), engine type, thrust rating and take-off thrust. However, an engine with a unique ESN may be tested for different thrust rating, each with different thrust levels. The engine rating and take-off thrust attributes therefore could contain more than one value. This introduces two problems. First, there is no way of telling which take-off thrust belongs to which thrust rating, and second, searching engines with specific thrust ratings becomes difficult and inefficient. Although a seemingly easy solution could be to use multiple records for the same engine with different thrust ratings, this causes data duplication.

To be in the first normal form (1NF), all repeating groups are eliminated from each table. For this example the solution would be splitting the Engines entity in two tables; one containing the ESN and engine type, and one containing the thrust rating and corresponding take-off thrust. This leads to a one-to-many relation between the two tables, that is, one engine can have many thrust ratings.

Even though 1NF database relations prevent several problems by not having repeating groups, other potential problems that may arise when the relations are not in 1NF are: *insertion anomalies*, *deletion anomalies*, and *modification anomalies*. These problem occur because a particular table may be in contradiction with the integrity principles of the relational database model. It is the DBMS, which guards the integrity of a database, that prevents insertions and deletions that violate the relational model. Modification anomalies originate from unnecessary duplicated data. A detailed explanation of these anomalies is beyond the scope of this thesis. The interested reader is referred to texts by Harrington [21] or Date [9].

The second normal form states that *in addition of being in 1NF, all non-key attributes are functionally dependent on the entire primary key.* A functional dependency is one-way relationship between two attributes which states that for each unique value of attribute A, there is only one value of attribute B associated with it via the relationship. Consider for example, again the Engine table in figure 6.1. A unique value for the ESN attribute is related to only one value of the engine type attribute: the engine instance with ESN value of 123456 is related to engine type value of 'CF6-80C2'. In this relationship the ESN is the *determinant*: the attribute that determines the value of other related attributes. When all determinants are used as primary keys of the database relations, the database is in 2NF.

Database manipulation problems may still arise when the relationships are in 2NF. Consider for example the Engine table with three additional fields containing information about the aircraft on which it is installed and the position on the aircraft.

Engine(ESN, engine type, aircraft registration, engine position, aircraft type)

Although this relationship is in 2NF, there is an insertion anomaly: data about the aircraft can only be inserted when an ESN is known, there is a deletion anomaly: deleting the only engine on an aircraft deletes all information about that aircraft, and there is a modification anomaly: for each additional engine installed on one aircraft the aircraft registration information is unnecessary duplicated. This table contains information about two related entities.

The third normal form, which is designed to handle situations just described, states that *in addition of being in 2NF, there are no transitive dependencies.* A transitive dependency is a functional dependency occurring in relations with three or more attributes. Mathematically this may be described as:

$$A > B\, and\, B > C;\, therefore\, A > C$$

The only reason that the aircraft type was functionally dependent on the ESN was because the aircraft registration was functionally dependent on the ESN and the aircraft type was functionally dependent on the aircraft registration. However, the functional dependencies are:

$$ESN \rightarrow engine\, type, engine\, position$$

$$Aircraft\, registration \rightarrow aircraft\, type$$

The additional normal forms: the Boyce-Codd normal form, the fourth normal form, and the fifth normal form are necessary for special relation ships where anomalies may still occur when in 3NF. However, the GPA database concept did not contain any special relationship for which additional normalization was required.

6.3 Information analysis

Information analysis is the phase in the database design process to establish aspects such as what data are available, the purpose of the database, and the information that the database should deliver. This step will affect what data will be stored, the structure of the database, and ultimately determines the quality of the database.

Systematic use of GPA in the turbofan maintenance process requires measured performance parameters for gas path diagnostics, and maintenance-related data to relate maintenance actions to gas path component condition. The necessary data originates from different sources and must be stored in the database in a consistent format. Additional data analysis may be used for discovering valuable knowledge for the maintenance process. The flow chart in figure 6.3 shows this information flow and some components of the information system.

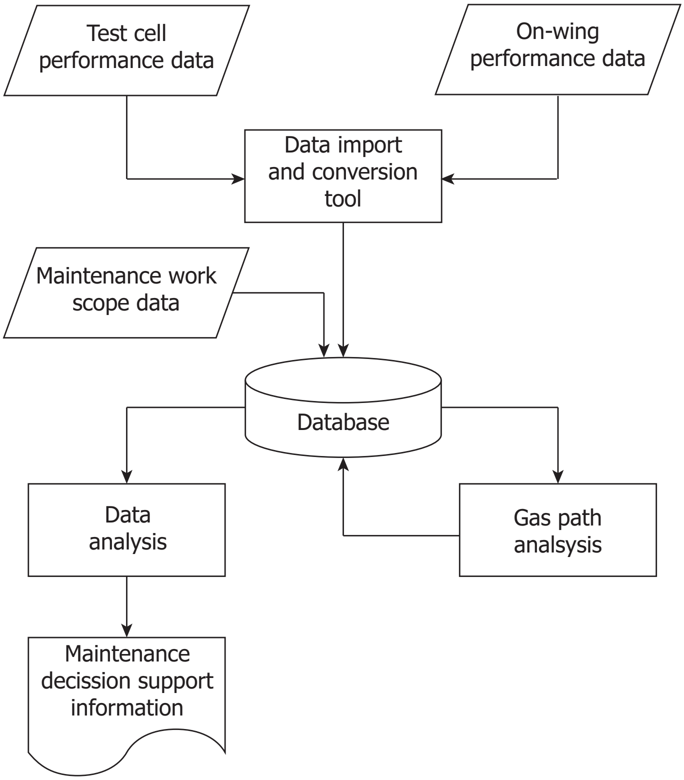


Figure 6.3: *Flow chart showing the information flows to and from a centralized database. The objective of collecting, storing and analyzing this information is to generate valuable knowledge for the turbofan maintenance process.*

6.3.1 Engine performance data

During the operational life of a turbofan engine, performance data are recorded on-wing (in-flight) for condition monitoring and on the ground in an engine test cell usually after engine overhaul. Of these two performance data sources, the test cell provides the most accurate performance snapshot. In addition to the observed performance parameters, performance margins and other corrected parameters are calculated that are indicative of overall engine condition, fuel efficiency, and remaining performance life. Each post-overhaul performance tests at KLM provided performance data at four different power settings.

For on-wing condition monitoring performance snapshots are recorded at different moments during each flight; one at a high power setting during take-off and one during cruise. Although exact protocols are defined for on-wing performance snapshots, the operating condition in which they are recorded may vary between flights. Moreover, not all performance parameters that are measured in a test cell may also be measured on-wing. This depends on optional sensors that may or may not be installed for on-wing condition monitoring.

Because test cell and on-wing measured performance data come from the MRO shop and the engine operator respectively, they may use different units and parameter names. Moreover, the performance data may be available in different formats. Indeed, at KLM the test cell and on-wing performance data used different parameter names, units and data formats. However, the GPA database used the standard gas path station naming convention and SI-units. A data import tool was created for converting engine performance data from both sources and import them into the database.

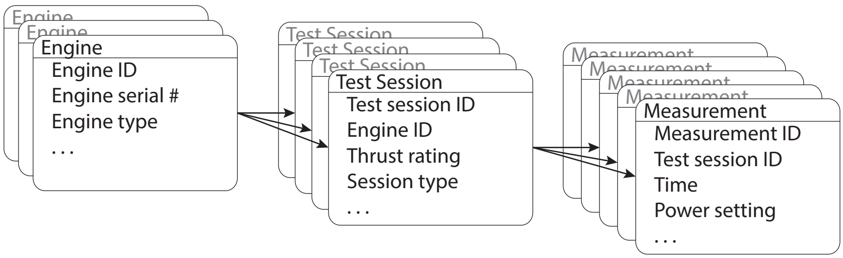


Figure 6.4: *One engine, may be related to many test sessions, each of which may be related to many measured data sets.*

All performance data measured in a test cell or on-wing ultimately belongs to a specific engine with a specific engine serial number. Therefore, an *Engines* entity was defined for storing all necessary information for describing an engine. While the amount of observed performance parameters and power settings may vary, both sources may be viewed as similar sessions during which measured performance parameters are recorded. A *Test Sessions* entity was defined for storing all data relevant to a test session. Each Test Session instance always belongs to one engine instance. During each test session, one or more sets of measured performance data are recorded; one data set for an on-wing test session, and four data sets during a test sessions in a test cell. A *Measurements* entity was defined to store all relevant measured performance parameters. Each Test Sessions instance was related to one or more Measurements instances. The relation between Engines, test sessions, and measurements are shown in figure 6.4

6.3.2 Maintenance work scope data

Maintenance work scope data of engine overhaul was available from the engine shop. It contains information about whether a specific engine module, assembly, or part was maintained and states to what level it was maintained. For the GPA database concept only maintenance work scope data of gas path components was considered. Because on-wing maintenance actions usually do not affect gas path component performance, data describing on-wing maintenance actions was not considered at this point.

After overhaul an engine undergoes a mandatory performance test. For some engines multiple test sessions are necessary to certify it for the potential thrust ratings at which it may be operated. Consequently, the maintenance work scope performed during a shop visit may be related to multiple test sessions. Therefore, to store maintenance work scope data a *Work Scopes* entity is defined. Work scopes instances must always be related to one or more Test Sessions instances.

6.3.3 GPA data

Each record of *measured* performance parameters in the database may be used for GPA. A *GPA Results* entity may be defined for storing all relevant information generated with GPA. In principle each measurement set may lead to a single GPA result. This would lead to a one-to-one relation between the Measurements entity and a GPA results entity. However, to focus the diagnosis on specific gas path components the *dominant trend analysis method*[2, 52] may be applied. Using this method would result in multiple GPA results for a single measurement set, each obtained from different subsets of a Measurements entity. Implementing this method requires to a one-to-many relationship between the Measurements entity and a GPA Results entity.

The objective of the database concept was storing information that was relevant to the maintenance process. From a maintenance perspective, storing a single correct GPA result is sufficient. Therefore, a one-to-one relation was selected for the Measurements entity and a GPA results entity. Because of the one-to-one relationship, both entities were stored in a single database table.

Performance model calibration is one step in the Adaptive Modeling (AM) calculation that was used for GPA. Storing that information is important because it allows evaluating the validity of the GPA results. The *Cal Factors* entity was defined to hold information relevant to the model calibration step used in the AM calculation. Often a single measured data set of a specific engine is selected as a reference, which is then used for obtaining GPA results for multiple measured data sets. Therefore, a one-to-many relationship exists between the GPA Results entity and a Cal Factors entity. However, as each Cal Factor instance is obtained from a single measured data set, a one-to-one relationship exists between the Measurements entity and the Cal Factors entity.

6.3.4 GPA database tables and relations

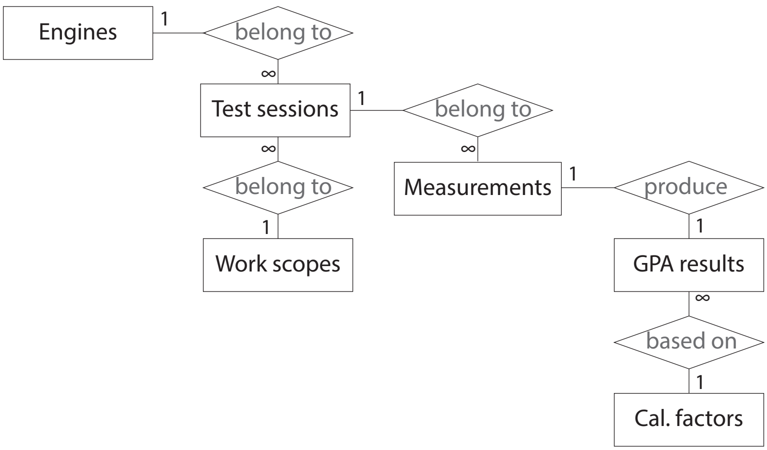


Figure 6.5: *GPA database entity-relationships diagram.*

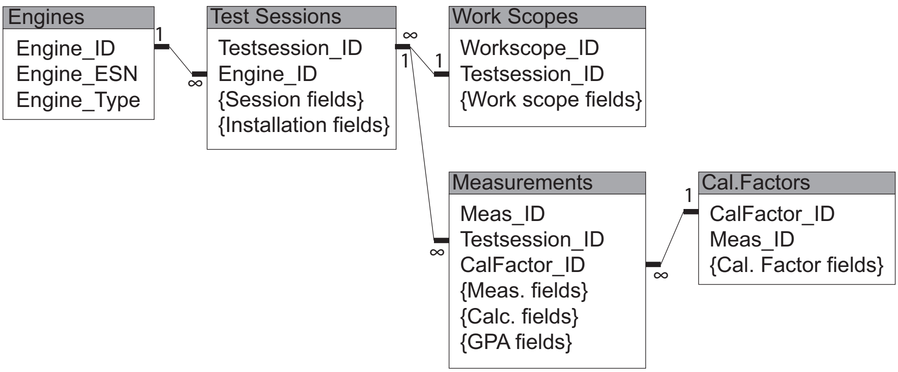


Figure 6.6: *An overview showing the tables, relations, and attribute groups for the GPA database concept.*

Figure 6.5 shows the entity-relationship diagram for the GPA database concept. Although 6 separate entities were identified during the information analysis and data modeling step, the GPA database concept contains 5 related tables. The one-to-one relationship that was identified between the Measurements entity and the GPA Results entity means that both entities could be combined into a single table. The final database concept is shown in figure 6.6. Not all attributes are specified for each table in this figure. Instead attribute groups are used to represent actual attributes of each table. The attribute groups are indicated by the curly brackets.

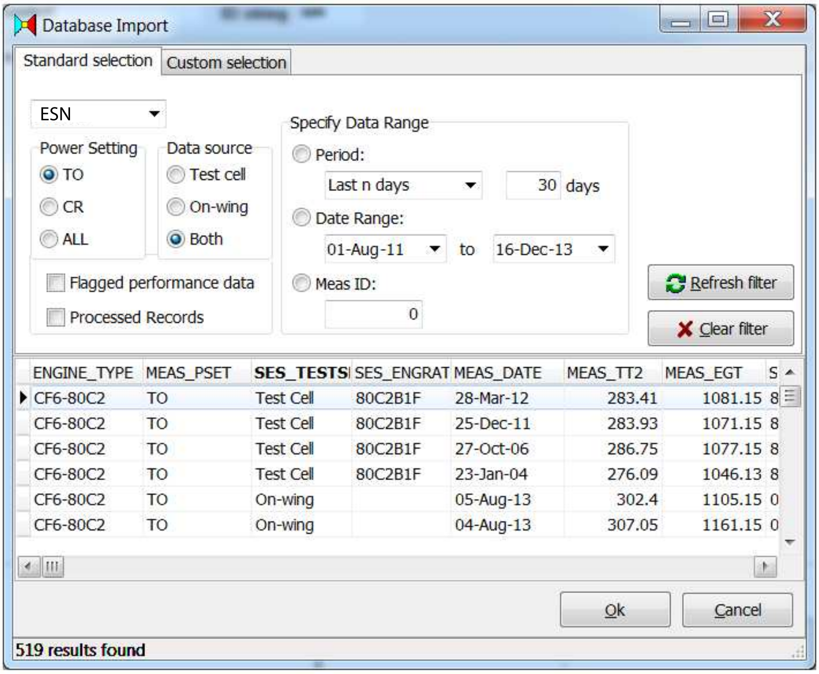


Figure 6.7: *Database import user interface of the GSP AM component.*

6.3.5 Implementation into the AM component

Based on the results of the information analysis step a single-user GPA database concept was created. A specialized data importing tool was developed for importing both test cell and on-wing measured performance data into the database. A database connection was established between the GSP AM component and the GPA database. SQL was used for updating the database and retrieving performance data with specified criteria from the database. Figure 6.7 shows a screenshot of the window used for selecting performance data from the database. To select the required data set, the user can use a pre-defined query (figure 6.7) for which only data-specific criteria must be specified. The required SQL command was executed in the background. This option allows the user to focus on data specific information only. Alternatively, a fully customizable query can be used. This option allows maximum flexibility but requires the user to be familiar with the SQL syntax.

The interaction between the database and the AM component is not demonstrated in this chapter. The database was used in chapter 4 for retrieving performance data of engines with the best EGT margins. Those data were used to create average reference engine data sets. In chapter 5 the database was used for providing particular data subsets such as all engines of a specific thrust rating with all sensors installed, or all available on-wing measured performance data from a specific engine. GPA results were inserted in the database to create data cross-sections that showed interesting correlations between component condition deltas and engine performance margins. This work demonstrated the potential of systematically using GPA in combination with an effective information system.

6.4 Conclusion

GPA has been demonstrated as an effective method for estimating gas path component condition. GPA tools are often stand-alone computer programs with limited integration into the data of the aero-engine operational and maintenance processes. The GSP AM component that was used in this research initially required text files for automatically importing measured performance data sets or manual performance data input. No other maintenance-related data were used for further analysis. GPA results could only be stored in separate report files. While this capability was effective for analyzing relatively small data sets and reviewing the results, it limited the systematic use of GPA.

An information system concept was developed for the GSP AM component for systematic use of GPA in an aero-engine maintenance process. It was developed for the performance data that were available for this project. This concept, which implemented a relational database for storing relevant data available from the aero-engine maintenance and operational processes, was successfully coupled to the GSP AM component. It demonstrated the added value of systematically using GPA in the aero-engine maintenance process. The information system concept was used for studies presented in chapters 4 and 5. Using a relational database for storing data instead of individual text files offered benefits in terms of data accessibility and data analysis.

Better data accessibility was achieved by storing all data in a single relational database instead of being scattered among many individual text files. Using a relational database made searching for data sets easier and faster. It allowed the search to be based on any criteria that could be specified for the data in the database. In addition, coupling the GSP AM component to the database allowed for automated analysis of large data sets. This capability was particularly beneficial for analyzing large on-wing measured performance data sets.

The database contained measured and calculated engine performance data as well as GPA results. The ability of creating data cross-sections meant that correlating GPA results with maintenance-related data or engine performance data could point to otherwise hidden correlations that may be relevant to the maintenance process. In addition, the relational database was important for estimating an average reference data set and trending on-wing component condition.

Perhaps the most important benefit of using a relational database is its capability to be extendible without affecting existing data or relationships in the database. While this may not lead to better GPA results, including data from other relevant processes in the aero-engine maintenance process may offer new and potentially valuable insights. Those insights may provide just the right advantage in the competitive aero-engine maintenance business.

CHAPTER 7

General conclusions

This study was set out to investigate how gas path analysis can be more effectively used in the maintenance process of gas turbine aero-engines. Maintenance is an expensive but essential activity that ensures safe, reliable, and cost-effective airline operations. To maximize an engine's time on-wing at minimal cost, condition-based maintenance is used. This maintenance strategy requires regular inspections, engine condition monitoring and other diagnostics methods to establish the degree of deterioration. GPA is a method that can be used to identify engine modules responsible for aero-thermodynamic performance-related problems. This makes it an excellent addition to the diagnostic methods used for condition-based maintenance. Despite being recognized as a valuable tool by many in the gas turbine community and in the maintenance, repair and overhaul industry, systematic use of GPA in the aero-engine maintenance process remains limited.

The work presented in this thesis was focused on three main subjects. The first subject was improving the accuracy and reliability of a non-linear, model-based GPA tool. The second subject was more effectively using available engine performance data for GPA. The third subject was developing an information system concept for integrating GPA in an aero-engine maintenance process. While this study used performance data of gas turbine aero-engines only, the similarities with land-based and marine gas turbines in terms of operational and maintenance concepts means that the methods, results and conclusions presented herein apply to gas turbines in general. Chapters 2-6 contain detailed conclusions on this work. Overall, the following can be concluded on the main subjects covered in this thesis:

- **Accuracy and reliability** The effects of measurement error cannot be eliminated from GPA results. However, the effects of random sensor errors are relatively small compared to errors originating from incorrect model calibration and missing gas path pressure and temperature measurements. When proxy parameters are used as an alternative for missing pressure or temperature measurements in the gas path, measurement errors can lead to high uncertainty for some condition parameter deviations. The effects of systematic errors can be reduced significantly by correct model calibration. It was demonstrated that despite the presence of both random and systematic measurement error, component condition estimations that are sufficiently accurate for maintenance application can be obtained when GPA is used for an extended period.

Component maps available in the public domain that are tuned by using a large volume of measured performance data are better suited for GPA applications than those scaled relative to a single operating point. The accuracy of model-based GPA results is strongly dependent on the used reference data set and the correct model calibration method. Using a single, fixed reference data set to analyze multiple engines of the same model introduces errors. An effective approach for practical application in the aero-engine maintenance process is to define an average reference data set based on multiple reference engines with good overall performance. In addition to providing a more accurate estimate of component condition deviation, this method also allows visualization of otherwise unknown uncertainty in condition parameters and thus enables judging the validity of the results.

- **Effectively using available engine performance data for GPA.** Using GPA for on-wing component condition monitoring provides much more detail than performance monitoring methods that are often used for monitoring commercial turbofan engines. In addition, when used systematically this approach provides valuable information for the maintenance process prior to engine removal. When too few measured performance parameters are available for detailed GPA, adapted-model performance analysis can be used to analyze engines that show abnormal performance. This way GPA is used indirectly for analysis of measured performance parameters that are available.

- **Information system concept for GPA application.** Stand-alone GPA tools limit systematic application in the condition monitoring and maintenance processes of aero-engines. Storing measured performance data as well as the GPA results in a single relational database instead of many individual files made identifying relevant trends easier and faster. The added value of the information system concept and systematically using GPA in the maintenance process has been demonstrated on a large fleet of commercial turbofan engines. One benefit of using a single database containing all relevant data was the ability to identify systematic performance measurement errors with a constant bias by comparing long-term performance and condition monitoring data from multiple engines.

It is important to keep in mind that gas turbine part repair and replacement are dictated solely by the engine repair manual. While engine removal and overhaul can be triggered due to performance loss, the findings from performance diagnostics have little effect on whether or not parts must be replaced. However, the unique ability of GPA to identify gas path components with poor condition helps to reduce unnecessary repair of components that still perform adequately. This implies that identifying to correct gas path components with relatively poor performance is more important than accurately estimating the degree of condition deterioration.

The results obtained from this study have demonstrated that GPA can be used more effectively in the maintenance process of gas turbines when it is used systematically to analyze operational and post-overhaul performance data. This way engine condition can be monitored with more detail than traditional performance monitoring methods. But more importantly, the GPA information available prior to overhaul enables estimating cost-effective maintenance work scope to restore engine performance to a desired level.

Maintenance is inevitable as a gas turbine aero-engine ages. Although modern turbofan engine models are newly built with large EGT margins, and engine removals due to performance loss have been greatly reduced over the years, the matter of guaranteeing post-overhaul engine performance levels remains a very important issue in the engine overhaul business. Financial consequences of failing to meet performance warranties can be very significant compared to the cost of engine overhaul. It has demonstrated that GPA is a valuable addition to existing diagnostic methods that are used in the maintenance process of gas turbine aero-engines. Performance diagnostic methods are a fundamental part of engine overhaul practices. When used systematically they help minimizing aero-engine maintenance cost and the risk of failing to meet post-overhaul performance warranties.

Nomenclature

Latin Symbols

ΔWc	Flow capacity deviation	[%]
f_c	Calibration factor	[-]
h_t	Total specific enthalpy	$[Jkg^{-1}]$
D	Characteristic diameter	[m]
N1	Low pressure shaft rotational speed	[RPM]
N2	High pressure shaft rotational speed	[RPM]
Nc	Corrected shaft speed	[%]
P	Pressure	[bar]
P0,Pt	Total/stagnation pressure	[bar]
PR	Pressure ratio	[-]
Ps	Static pressure	[bar]
R	Specific gas constant	$[\mathrm{J\,kg^{-1}K^{-1}}]$
RH	Relative humidity	[%]
T	Temperature	[K]
T0,Tt	Total/stagnation temperature	[K]
Ts	Static emperature	[K]
W,$\dot{m}$	Mass flow	$[\mathrm{kg\,s^{-1}}]$
Wc	Mass flow capacity	[-]
Wf	Fuel mass flow	$[\mathrm{kg\,s^{-1}}]$

Greek Symbols

β	Component map auxiliary coordinate	[-]
δ	Ratio of pressure and standard pressure P/P_{amb}	[-]
$\Delta\eta$	Efficiency deviation	[%]
η	Isentropic efficiency	[-]
ν	Viscosity	[$\mathrm{kg\,m^{-1}s^{-1}}$]
θ	Ratio of temperature and standard temperature T/T_{amb}	[-]

Subscripts

$_0$	Ambient
$_{14}$	Fan bypass exit
$_1$	Inlet
$_{25}$	Booster/intermediate compressor exit
$_2$	Compressor inlet
$_3$	High pressure compressor exit, combustor inlet
$_{45}$	High pressure turbine exit
$_4$	Combustor exit/high pressure turbine inlet
$_5$	Low pressure turbine exit
$_9$	Exhaust nozzle exit
$_c$	Core engine
$_{d,bp}$	Fan duct or bypass

Abbreviations

AFI Air France Industries
AI Artificial intelligence
AM Adaptive modeling
ANN Artificial Neural network
ASCII American Standard Code for Information Interchange
ASME American Society of Mechanical Engineers
CDP Compressor discharge pressure
CHP Combined heat and power
DBMS Database management system

DOC Direct operating cost
ECM Engine Condition Monitoring
ECU Engine control unit
EGT Exhaust gas temperature
EHM Engine health management
EPCOR European Pneumatic Component Overhaul and Repair
ESN Engine serial number
ES Expert system
ETOPS Extended range operation with two-engine airplanes
EWMA Exponentially weighted moving average
FADEC Full Authority Digital Engine Control
FCM Fault coefficient matrix
FNK Corrected thrust
GA Genetic algorithm
GE General Electric company
GPA Gas path analysis
GSP Gas turbine simulation program
HCF High cycle fatigue
HD Hot day conditions
HPC High pressure compressor
HPT High pressure turbine
IATA International air transport association
ICM Influence coefficient matrix
ISABE International Symposium on Air Breathing Engines
KLM Royal Dutch Airlines
LCF Low cycle fatigue
LLP Life-limited parts
LPT Low pressure turbine
MC Maximum continuous thrust
MM Map modifier factor
MRO Maintenance, repair, and overhaul
NF Normal forms
NGV Nozzle guide vane
NLR National Aerospace Laboratory of the Netherlands
OEM Original equipment manufacturer

PMC Power Management Control
RMS Root mean square
RPM Rotations per minute
RTD Resistive thermal device
SFC Specific fuel consumption
SQL Structured Query Language
TCDS Type certificate data sheet
TO Take-off thrust

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Curriculum Vitae

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Conference publications

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