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A COMPARISON OF MANAGEMENT APPROACHES FOR ASSET OPTIMIZATION

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ABSTRACT

As the energy landscape evolves and becomes progressively challenging for industrial gas turbines, OEMs are expected to support increased flexibility, maintain reliability, ensure availability all while reducing total cost of ownership. These competing requirements have led OEMs and even some third-party suppliers, to develop asset management tools to allow owners and operators to optimize the operation of their engines and manage service intervals, maintenance costs and performance levels. These tools are typically developed by the OEMs as a way to manage their equipment and are subject to the providers intellectual property but do fall into several high-level categories which can be compared. These categories include the traditional time-based approach, or time between overhaul (TBO), in which service intervals and maintenance costs are pre-determined by the OEM and are based on design specifications and overall experience. The equivalent operating hours (EoH) approach, in which the operator uses equations provided by the OEM to determine the remaining useful life of the engine based on key operational parameters, such as engine starts. Finally, the true condition-based approach, in which the operating conditions of the engine determines the remaining useful life as a function of the nonlinear nature of damage accumulation. This paper compares and contrasts these different approaches to highlight the advantages and disadvantages relative to current applications. The paper also provides a speculative view of how these approaches will perform in the future as the energy market changes.

INTRODUCTION

The operating environment inside of a gas turbine is one of the harshest environments that materials are subjected to. Careful selection of geometry and material is key to a successful turbine. Determining when a turbine is due for a major service can be equally as challenging. Historically, turbine manufactures have used actual operating hours or various equivalent operating hours calculations to determine when turbomachinery equipment should be serviced and overhauled. Today, with the advancements in material science, predictivity models, digital technology and remote monitoring capability, there is a viable third option of calculating the true Remaining Useful Life (RUL) of components based on the specific conditions of operation. This condition based approach to asset management requires the development of a robust data collection and processing system and a digital twin of the physical asset under consideration all combined under the framework of people, process and technology.

One of the challenges with predicting RUL is the non-linear nature of material behaviour inside a gas turbine. This is a challenge as the digital model must produce accurate and repeatable predictions in order to make important operational decisions. This paper focuses on predicting the durability of turbomachinery. Performance losses due to degradation or foiling are not covered in this paper. This paper discusses the advantages and challenges with the use of predictive analysis based on operating data.

NOMENCLATURE

RUL	Remaining Useful Life
PBM	Physics-Based Modeling
iIot	Industrial Internet of Things
N_i	Life to Crack Initiation
ROM	Reduced Order Model
FEA	Finite Element Analysis
EHM	Equipment Health Management
CFD	Computational Fluid Dynamics
λ	Damage Accumulation
OEM	Original Equipment Manufacturer
t_i	Time to crack initiation
PDF	Probability Density Function
TBO	Time Between Overhauls (service interval)
T_m	Metal Temperature at Specific Locations
ε	Strain

DEFINING DIFFERENT APPROACHES TO ASSET MANAGEMENT

Before any evaluation of the different approaches to asset management is undertaken, a clear definition of the approaches is required into order to establish a baseline for comparison. The following sections outline the authors definition of the different approaches and is intended to act as a basis for comparison. The following definitions are not intended to be a comprehensive overview, as such an undertaking would require in depth knowledge of all OEM and third-party methods and processes. The definition is intended to provide a general overview and specifics of application will be different depending on the design and asset management philosophy of each OEM or third-party supplier.

Time Based Approach:

The ubiquitous time-based approach is the definitive baseline from which assets have been traditionally managed. The approach uses the linear accumulation of time during operation as a surrogate for damage accumulation (λ) to a predetermined remaining useful life, (RUL). The rate of damage accumulation is defined during the design phase of the engine and often takes a pragmatic approach to engine life. In the case of new engine designs the design engineers require boundary conditions in order to establish the design and achieve the desired engine characteristics, such as output power, efficiency, emissions, durability and cost. As there is no specific engine data to reference at this stage of the design cycle, the engine is designed for the intended application based on experience. The balance between operational flexibility and product cost is critically important at this phase of the engine development. A design which is intended to meet all aspects of operation will inevitably be at the expense of product cost, therefore a balance is struck between desired functionality and cost.

Durability is defined around targeted service intervals, (i.e. 30k hours between engine exchange) for the most arduous operation or duty cycles the engines can be subjected to during operation. Probability of the engine undergoing a particular type of duty cycle during operation can often be leveraged based on experience. However, because the design engineers are designing for all applications, they need to consider the worst-case scenario to ensure the engine will achieve the targeted service interval with the highest probability of success and the maximum possible damage accumulation.

The advantage of this approach is typically a highly robust design with a high confidence that the engine will meet the targeted service interval. If the initial assumptions around operation and applications are accurate and the use cases do not change over time, the approach is sound and does not require further interpretation. The asset management approach for the engine simply becomes a function of time and the damage accumulation (λ). Remaining useful life (RUL) is assumed to be linear, (as the increment of time is a constant, C). Figure 1 illustrates this concept

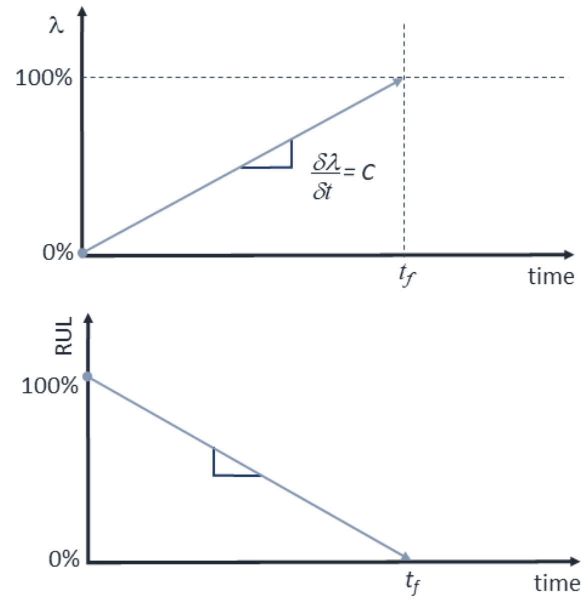

Figure 1 Illustrates the linear interpretation of damage accumulation and subsequently the remaining useful life for a traditional time based approach.

Confidence to achieve design objectives increases with experience through the observed physical component condition over the accumulated life of multiple units within a fleet. This empirical approach to design validation and asset management has clear advantages, but also significant drawbacks. If the owner / operator requires more operational flexibility to meet changing demands of an evolving market, then this approach is limited in that it is not predictive. The approach is principally based on assumption at the design phase and despite the inherent conservatism, leveraging this conservatism to support changes in operation from the initial assumptions is qualitative at best. This is because the original design assumptions do not support an incremental approach to damage accumulation. As discussed, damage accumulation in an industrial gas turbine is typically nonlinear and therefore path dependant. Any attempt to employ the conservativism from the design approach will be based on experience and engineering judgment and will not be specific to that application. This approach is still valid, has tremendous value and has served our industry well in the past. However, this approach is qualitative, general and not prescriptive. Therefore, any deviation from the initial design assumptions would need to be quantified in order to gain greater confidence in the prediction to truly optimize the engine for a specific application. To achieve this, a discrete method to incrementally accounting for changes in operation is required, such as those described on the following sections.

Equivalent Operating Hours:

A method to account for incremental changes in operation is provided by equivalencing off design conditions by a factor that can be applied to the hours in operation. For example, if a single shaft engine operates at a part load condition, the thermal load on the engine is reduced as less fuel is applied to provide the required load. The lower load equates to lower temperatures in the hot section of the engine and this will help to reduce the damage accumulation for key components in the turbine such as disks, nozzles and blades. The difference in the accumulated damage for both the full load and part load condition can be factored by dividing the damage accumulation at part load condition by the damage accumulation at full load.

$$\frac{\lambda_{part\ load}}{\lambda_{full\ load}} = Factor$$

The resulting factor can be applied to time spent at this part load condition. In order to apply this approach, the damage fraction first needs to be determined as a function of the total time to reach 100% damage. The total damage in question is a function of the damage mechanism and may not be necessarily catastrophic, therefore the risk aspect of the damage needs to be considered and will be addresses later in the discussion. However, if creep was the damage mechanism in this example, then 100% would represent cracking for a localized feature in the component. The subsequent damage fraction would therefore be a function of damage per hour

$$\frac{1}{t_i} = \lambda_{creep}$$

It is important to note that this approach does not account for variations in the stress state of the component due to cycling. Therefore, the approach may not capture the full extent of the damage accumulated, for example additional damage due to primary creep persistency, (Green, R. et al, 2018) which can be addressed with a true condition based lifing approach.

This approach can also be applied to damage mechanisms which are not measured in the time domain, such as fatigue. Damage accumulation from fatigue is measured in the frequency domain and as such requires a translation function to be applicable in the time domain. The translation function can be as straight forward as a normalized damage fraction for a given damage mechanism or a parameter common to the active damage mechanisms. An example of the former application would be to calculate the incremental damage accumulation as a fraction for a given load condition, i.e. under typical load conditions, such as full load (design point) the component in question may have a finite number of major cycles, (engine starts and shutdowns) to initiate a fatigue crack. The damage fraction for each cycle is one over the total numbers of cycles to crack initiation,

$$\frac{1}{N_i} = \lambda_{fatigue}$$

In this approach the effects of shakedown due to isotropic and kinematic hardening are inherent in the damage fraction but are not explicitly considered in the calculation. This nuance is important as it demonstrates the fundamental difference between this approach and the condition base lifing approach discussed in the next section. Once converted to a damage fraction, the effects of cycles can easily be converted to equivalent hours by comparing the damage fraction to the time-based damage mechanisms, such as creep.

As an example, if a component has 10,000 typical engine cycles (start up and shutdown) to crack initiation at a full load (design point) condition then the damage fraction per cycle is 0.01%. If the pure creep life of the same component is 50,000 hours, then the damage fraction per hour is 0.002%. Therefore, the equivalent damage per hour for each cycle is a simple ratio of the damage fraction;

$$\frac{\lambda_{fatigue}}{\lambda_{creep}} = EoH$$

This results in factor of 5 for this example, which means that each engine start would be equivalent to 5 operating hours at full load.

This calculation can be completed for various types of cycles, such as fast starts or emergency shutdowns and linearly accumulated over the operation of the engine. Combining this equivalency with the part load factor discussed previously, provides a calculation for determining equivalent operating hours. This approach can be used to determine a baseline by the OEM. The baseline would typically assume some combination of starts (cold starts, hot restarts, emergency shutdowns etc.) and operating load profiles, to define a standard service interval, such as 30,000 hours. This allows the owner / operators to account for changes to the remaining useful life of the turbine if the operation deviates from the baseline.

It should be noted that this is a general overview of the equivalent hours approach and is for discussion purposes only. It is not intended to be a comprehensive review of all the OEMs and 3rd party applications of this approach. OEMs and third-party suppliers have versions of this approach imbued with intellectual property specific to that companies' products and offerings. It is clear however that this general approach can effectively be used to manage variations in engine operation and provide a path to optimizing the asset. This approach can be applied to either determine the remaining useful life of an existing asset or be applied as a forecast to help ascertain the optimal timing for a service interval. Figure 2 illustrates how changes in operation can generate specific remaining useful life curves for different operational profiles.

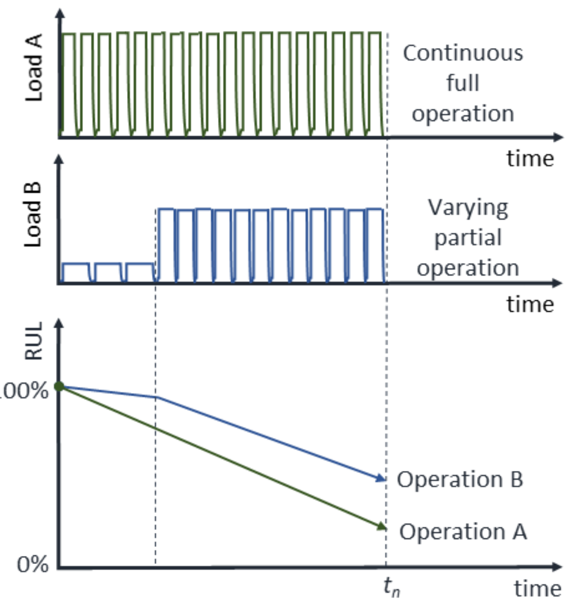

Figure 2 Illustrates how the equivalent operating hours can be applied to generate specific RUL curves for an engine with different operating profiles

As a method for predicting or evaluating different operational profiles, the equivalent operating hours approach has been effective, but has several drawbacks.

The immediate issue with equivalencing different aspects of operation as a factor is the potential complexity in application. Often a series of equations, factors and constants are provided by the OEM or 3rd party supplier to determine the impact of any deviation in operation on the timing of the targeted or baseline service interval. The more varied the operation the more complex the calculation which can be difficult to track if the intended operation changes frequently. Therefore, a system to track and update the operation based on historical data and forecasting is necessary to dynamically optimize operation. This can be challenging for customers, if this aspect of asset management is not included as part of an equipment health management service.

Furthermore, the approach does not implicitly account for the nonlinear behaviour of damage accumulation. The factor is determined as a constant increment of the response and therefore assumes the subsequent damage response is linear. This is the practical aspect of the EoH approach, in that for the approach to work the factor needs to be a constant that can be applied at any point in the life cycle of the engine. A factor that changes with damage accumulation would require path dependency Figure 3 illustrates this concept by comparing the response from a true linear response, (A) with a response (B) that is defined by applying different factors (B1, B2 & B3) to generate a pseudo nonlinear curve.

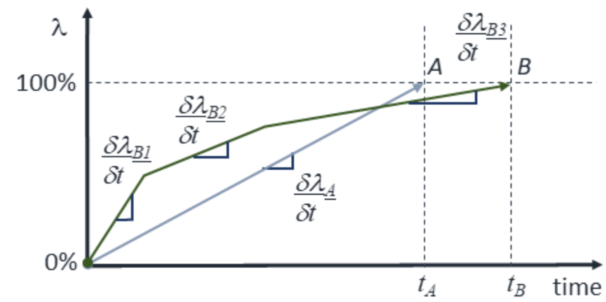

Figure 3 Shows, linear (A) and one nonlinear (B) response. The slope of the linear response is constant, the slope of the nonlinear response varies with the path of the response.

The incremental application of the factor is disassociated with the path dependency of the damage accumulation. That is to say that as a constant, the factor is the same at the initial onset of damage as it is for the final point of manifestation, such as crack initiation. The applicability of this assumption will vary depending on the damage mechanism in question. For damage mechanisms governed by linear behaviour, such as elastic fatigue, this is typically not an issue. However, in situations where the damage mechanisms are affected by inelastic behaviour, such as elastic / plastic fatigue or creep, the damage accumulation is typically nonlinear and as a result will be path dependant. Therefore, the magnitude of the factor will vary with damage progression. Figure 4 illustrates this concept with a simple creep curve which shows the nonlinear damage accumulation over time for a constant load.

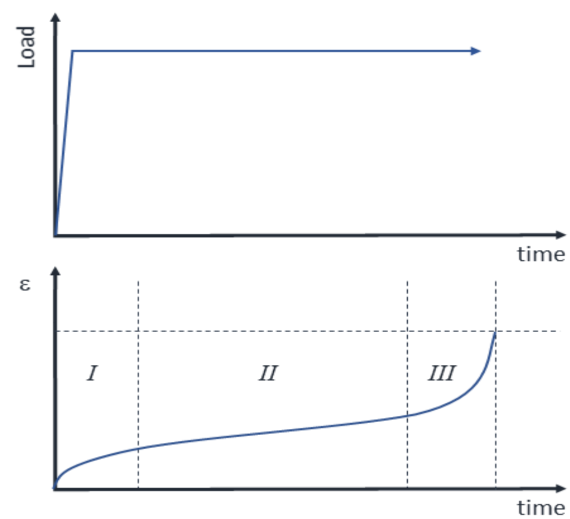

Figure 4 illustrates the variation in creep damage over time and demonstrates that the damage accumulation factor will also vary as the damage increases

Determining the most appropriate factor can be a challenge in order to safely account for the nonlinear behaviour. To ensure that the factor represents the highest rate of damage during the nonlinear response, the factor should be defined from the tangent of the steepest section of the nonlinear curve. This could lead to significant conservatism during the remainder of the response, resulting in an over prediction of damage throughout the full life cycle of the component.

If the assigned factor does not account for the highest gradient in the nonlinear response, the risk is that damage maybe underpredicted during part of the life cycle. This may not be a significant issue in the case of a single damage mechanism resulting from a simple, consistent load cycle. However, if the load cycle is complex, as discussed, damage mechanisms can interact. If the interaction occurs during the under predicted portion of the curve, the accuracy of the prediction could be adversely impacted, especially if this occurs early during the damage accumulation as the path dependency will compound the inaccuracies over the life of the application. Again, the recommended approach would be to introduce additional safety factors to compensate for the potential inaccuracies. As discussed, accurately defining these additional safety factors can be challenging and the tendency will and should be to err on the side of caution, resulting in additional conservatism. Figure 5 illustrates the challenge of identifying a suitable factor for two sperate nonlinear damage accumulation (creep) curves, (A) and (B). In both cases, factors can be defined for various aspects of the curves, the average overall factor, (EoH 1), or factors based on the steady state (II) portion of the creep curves, (EoH 2) which is typical for design. It is worth noting that in both examples the factors do not cover the maximum damage accumulation gradients and as discussed, would require a sufficient safety factor in order to avoid the aforementioned uncertainty due to potential interactions between damage mechanisms.

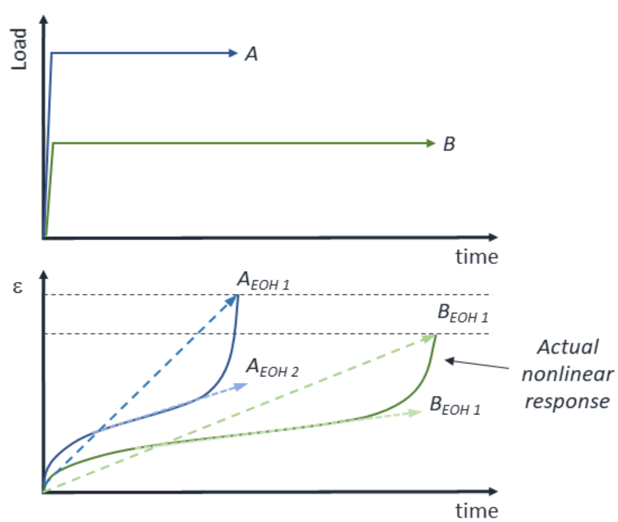

Figure 5 Illustrates the challenge of selecting an appropriate factor to represent nonlinear damage accumulation

Several studies on the interaction of key damage mechanisms have shown that the damage accumulation can be significantly affected when more than one damage mechanism is active in a given component during operation. Interactions are particularly challenging for industrial gas turbines due to the nature of the operation. A typical operational profile for an industrial gas turbine will be multiple cycles from load excisions to engine starts and shutdowns, leading to fatigue damage and extended periods at load, resulting in creep damage. The combination of these damage mechanisms can lead to creep fatigue interactions which can accelerate damage due to perturbations. Green, R. et al, 2018 & 2019 have shown that creep - fatigue interactions can yield much higher damages than either damage mechanism can contribute independently and figure 6 illustrates how introducing cycles can perturb stress relaxation due to creep.

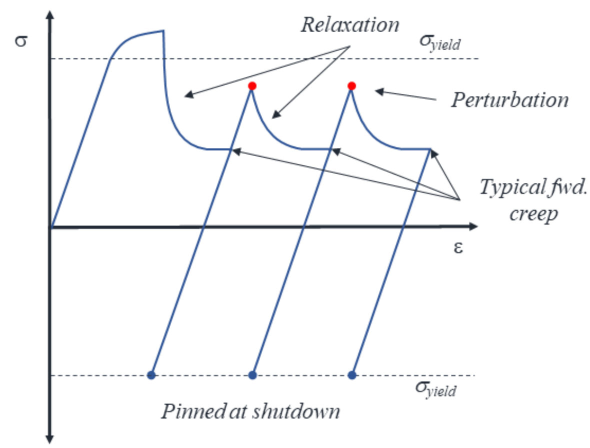

Figure 6 illustrates how creep can be perturbed by cycles, reintroducing additional relaxation and increasing creep damage.

This phenomenon is well documented for broader industrial applications, (Webster, G.A. & Ainsworth, R.A., 1994) and is taken into account for structural integrity codes such as R5 as outlined by Ainsworth, R. A., et al, 2006 & 2014. The implication for factored approaches, such as equivalent operating hours, is significant, especially given the potential severity of omitting this aspect of damage accumulation.

As discussed, previously, a constant factor or linear approach cannot explicitly account for path dependency and therefore these potential interactions are often accounted for implicitly through additional factors of safety. The implicit nature of accounting for this type of material behaviour in the model will and should lead to conservatism. The presence of additional conservatism in the model will limit the extent to which the engine or asset can be optimized.

Condition Based Lifing:

A true condition based approach is an evolution from the equivalent operating hours approach and attempts to explicitly account for path dependency in the damage accumulation. As in the equivalent operating hours approach, the condition based approach considers the incremental state of the engine by using the engines operational parameters, such as temperatures, pressures and speeds, as inputs to the damage calculations for the key components and subsystems which govern durability. Figure 7 illustrates how the condition based approaches compares in principle with the equivariant operating hours approach

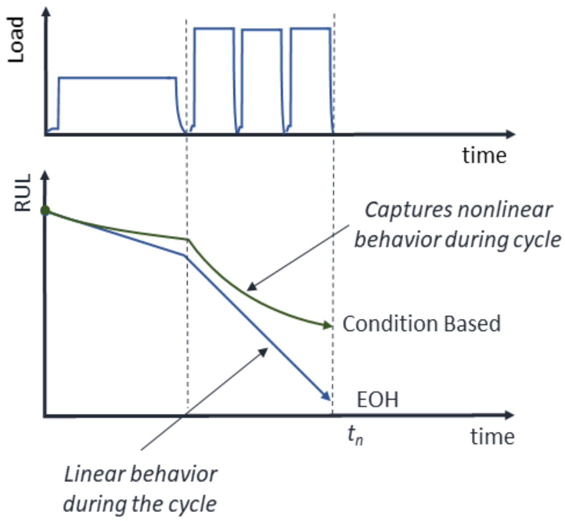

Figure 7 Comparison of a condition based and equivalent hour approaches

By calculating the incremental damage accumulation in this way, the full path dependant history can be determined and built explicitly over time without the need for additional conservatism. Interactions between damage mechanisms can be quantified at the moment of occurrence, capturing the impact as operation changes. Furthermore, this capability can be extrapolated to provide insight into the future state of the engine due to changes in operation. For example, an owner / operator has multiple units but wishes to shut a specific unit down for maintenance, they can assess the impact of increasing the load sharing between the remaining units. Knowing the exact state of each unit and the impact of increasing load, it is possible to optimize the operational load split and timing to achieve the required service interval for all machines before the event occurs. This forecasting capability is extremely valuable to be able to effectively optimize schedules and budgets without adversely affecting availability or reliability for production by allowing the users to build, test and evaluate multiple scenarios before the optimal case is executed. Having the ability to evaluate the machine in this way opens the potential for more advance analytics without the traditional need for extensive instrumentation. As the condition based approach is based on physics and fundamental material behaviour, it does not require advanced analytics to understand the relationships between operation and material degradation. Furthermore, analytics require training to be effective and as it is typically intolerable to allow a component to fail in operation in order to train an analytics model, it can be difficult to gain the necessary confidence in an analytic prediction to drive business decisions regarding reliability. Physics based (engineering) models are not limited in this way and do not require training. Physics models are bound, quantifiable and can be validated prior to implementation through the application of controlled testing and leveraging OEM experience from similar applications. This is extremely advantageous when owner / operators need the confidence to optimize the availability and reliability of their equipment. However, it should be noted that even the physics-based approach requires long term validation. OEMs such as Solar Turbines Incorporated, have access to multiple engines and components during engine exchange and overhaul. This provides a rich and valuable data source with which to validate and confirm model applicability. This fleet data can also be used to provide a broader, generalized understanding of durability which can be leverage across the entire fleet of engines.

The limitations of an analytics only approach is specific to durability, in that damage accumulation in an industrial gas turbine is difficult to quantify through physical indicators alone, such as borescope inspections. At the point at which the damage manifests to the degree that it can be witnessed, it is typically too late to effectively manage safety critical components for asset optimization, since the damage is already done. However, analytics when combined with a physics-based approach can be extremely effective. Taking a wholistic approach, analytics can be used to evaluate, track and help diagnose how operational characteristics and behaviours can influence durability and ultimately optimize reliability and availability.

Although condition based is the ideal for asset management, there are significant challenges to successfully implementing this approach. First and foremost is data collection and instrumentation. Condition based is data driven, and without a comprehensive source of data, the approach will be less effective. Data collection and processing is key and there are many considerations which should be addressed. Data quality, fidelity and availability are some of the elements specific to effective data collection. Data is measured from instrumentation, therefore the availability of instrumentation throughout the operational cycle of an industrial gas turbine is critically important. Balancing the availability of data with the effectiveness of the digital twin can be a challenge. Therefore, leveraging existing sensors to support the application of virtual sensors is one way to address the issue. The application of virtual sensors requires up front calibration, typically within a test environment, to ensure the virtual sensors are effective. Reliance on an effective and robust data management system is therefore critically important. Solar Turbines Incorporated have developed such a system through the InSight platform, which allows access to machine data through the PLC remotely. Systems such as these provide the fundamental data needed to drive the digital asset and supporting virtual sensors. These aspects are discussed in detail (Green, R., et al, ETN 2018) in the Overview of Digital Asset Management for Industrial Gas Turbine Applications.

As challenging as effective data collection and processing is, the data needs to be converted into inputs for the physics-based models. For example, to model the fatigue behaviour of a components accurately and effectively, the load cycles need to be defined. To define the load cycles, such as engine starts and shutdowns, the data collection system needs to capture the relevant transient parameters pertinent to the fatigue calculation, namely, changes in temperature, pressure and shaft speed which would influence the induced stress ranges during each cycle. If the data collection system does not have enough fidelity to define the full extent of the load profiles during the engine transient, the peak stress range maybe miscalculated and as such lead to significant inaccuracy in the fatigue damage calculation. Furthermore, if data quality or availability is an issue, this too could lead to inaccuracies which would compound over the assessment period, further eroding confidence in the ability to predict an accurate damage accumulation. However, assuming the data collection system is sufficiently robust, the challenge then becomes how to process this data in a reasonable time frame.

Operational data direct from the engine management system typically requires translation into input and boundary conditions for the damage calculation. Rarely can data be used directly to assess the structural integrity of a component given the nonlinear behaviour of the materials for most of the key damage mechanisms. In the above example, gas path temperatures, pressures and shaft speeds need to be translated into metal temperatures and stress tensors, which can be a challenge for complex geometries with non-uniform temperature distributions. Traditional engineering methods and tools, such as Computational Fluid Dynamics, (CFD) and Finite Element Analysis (FEA) are too computationally cumbersome to be practical solutions in this scenario. Although accurate to address the needs of the assessment, the calculations would take too long and require impractical computational resources for a typical industrial gas turbine data set, (i.e. years of on load operations with hundreds, if not thousands of cycles).

A solution to this problem is provided with the development and application of digital assets. A digital asset is a collection of reduced order physics-based models and analytics working in concert to act as a surrogate of the physical asset operating in the field. The key aspect of the digital asset is the reduced order models, which can perform the necessary calculations to simulate the traditional methods and tools, in almost real time with considerably less computational effort. Reduced order models have been developed for a variety of gas turbine applications, (van Paridon et al, 2014 & 2016).

Again, combined with analytic, this approach can provide the means for a digital asset to translate direct machine data into inputs and boundary conditions for damage calculations. As discussed in the previous reference, (Green, R. at al, 2018), the application of a digital asset is key to leveraging machine data for asset optimization, especially for managing durability. Therefore, the digital asset can take the large data set and translate the machine data into inputs and boundary conditions for the fatigue calculation in the above example. Once converted, the material responses can be evaluated against material curves, (for a range of temperatures) for that specific damage mechanism to be established as a damage fraction, which in turn can then be used to determine the remaining useful life for the component. In this example, the stress ranges for each cycle can be summarised with a Miner's rule approach to determine the damage accumulation over the operational period. This is a relatively straight forward solution to a relatively straight forward fatigue problem. The final challenge for the digital asset is addressing the issue of interaction between damage mechanisms.

As discussed in the previous section, the nature of industrial gas turbine operation leads to a likelihood that damage mechanisms will interact. Extended dwell periods at temperature, coupled with variations in engine operation including starts, load excursions and shutdowns may lead to creep / fatigue interactions. As these damage mechanisms are typically evaluated independently (creep is assessed in the time domain, fatigue is assessed in the frequency domain) a method for combing the damages from both mechanisms is necessary for an accurate prediction. There are many models available that can account for interactions and combine damage, such as ductility exhaustion, which is employed by Solar Turbines (US 9.200,984 B2). Whichever model or approach is chosen, it should be integrated into the digital asset to explicitly account for the damage from contributing mechanisms as well as damage due to the interactions between mechanisms. Furthermore, the digital asset should be capable of supporting all life limiting locations. Depending on operation, a critical component may have multiple damage locations depending on which damage mechanisms are typically active during operation. For example, a turbine disk may have locations susceptible to creep, fatigue and creep fatigue interaction. All locations need to be identified and evaluated to determine which location is limiting the life of the part at the time of the assessment. It is not unusual for the life limiting location to change over the course of the components life which may have a significant impact to the asset optimization philosophy. For example an engine operated at part load, (low temperature) with frequent starts (cycles) may be dominated by fatigue at a specific component and location, however, if the duty of that engine was to change during the service interval, where the operation moved to increased load (temperature) with fewer starts, the dominant damage mechanism may move to creep at a different location or even component. It is critically important that the digital asset have the capability to differentiate the effects of varying operation in this way in order to effectively predict durability.

This level of fidelity is crucially important for the approach to inspire sufficient confidence to make meaningful business decisions. Without the ability to do so, the approach would lose any benefits and purpose. It is therefore imperative that the physics and functionality of the digital asset is validated. There are a number of ways to verify and validate the functionality of the digital asset, the most challenging of which is the accurate prediction of key component temperatures within the turbine, especially during transient operation. Validating transient temperatures for rotating components can be challenging, however there are measurement technologies and techniques available, such as telemetry or slip rings, which can be employed to measure temperatures from embed thermocouples. These tests are complex and expensive but are necessary to quantify the uncertainty in the temperature predictions.

Finally, a method for managing the uncertainty in digital asset predictions is required in order to account for variations in the material behaviour, the sensor readings and the accuracy of the physics models. Developing a probabilistic model to encompass the digital asset is one such approach. Integrating probability distribution functions from a variety of sources to create an aggregate function can be challenging and requires knowledge and experience of the system to be effective and avoid compounding conservatism. There are many examples for OEMs and 3rd party suppliers developing these types of probabilistic systems, (Wang, L. et al, ASME 2011) to manage uncertainty. Further digital asset developments have seen the adaptation of these methods, (Cathcart, H. et al, ASME 2020) to support the application to industrial gas turbines.

The benefits of manging equipment to this level of detail are apparent in the opportunities afforded for true asset optimization. Understanding the implications of varying operation, from increasing firing temperature over the baseline rating (Power boost), to the relevance of part load application for life extension to optimize OPEX is very much dependant on the accurate and reliable prediction of component life. The development of a condition based approach, along with establishing the necessary supporting tools (digital assists) and systems, (data collection and monitoring), is a significant undertaking. However, this investment is necessary to ensure confidence in the decisions needed to truly optimize the asset.

COMPARING MANAGEMENT APPRAOCHES

Three high level approaches have been presented, outlining the typical methodologies, tools and techniques employed in managing industrial gas turbines. Variations on these themes exist and are specific to each OEM or 3rd party supplier. The intent of this paper is to provide a high level comparison only and is not intended to be a comprehensive evaluation of all applications of these management approaches. Each approach has distinct advantages and disadvantages and therefore a comparison is beneficial to help summarise. Table 1 provides an overview of the main benefits and drawbacks.

Approach	**Benefits**	**Drawbacks**
Time based	Understandable Easy to apply	Inflexible Conservative (safety factors) Requires experience to deviate from design Qualitative
EoH	Flexible Pseudo quantitative Semi optimal	Complicated Conservative (safety factors) Formula required
Condition Based	Flexible Accurate Quantitative Optimal	Complicated EHM required

Table 1: Summary table expounding the benefits and drawbacks for the three management approaches.

As can be seen from the summary table, the principal advantage of the time based approach and to a lesser extent, the equivalent operating hours approach is in the simplicity of the application. Owners / operators simply apply the time elapsed against the recommended service interval to determine the remaining operating period. In the case of the EoH, either the owner / operators or the service provider for equipment health management applications, will apply the necessary factor based on the type of operation, to determine the equivalent remaining operating period. As discussed, the latter case can become somewhat cumbersome in the event of highly variable operation. The drawback to both these approaches is the level of conservatism required to ensure the predictions are safe and applicable to all applications. This is especially true for the time based approach which relies on assumptions typically applied at the design phase. Again, less so for the EoH approach, which can take advantage of differing operating conditions to improve the applicability of the prediction. However, less conservative than the time based approach, EoH still requires liberal use of safety factors to manage the nonlinear behaviour.

The condition based approach addresses this later issue and provides the most comprehensive assessment of durability. Using a condition based approach, it is possible to effectively account for interactions between damage mechanisms and provide the most representative remaining useful life curve which can be used to identify and isolate the most damaging elements of operation. Furthermore, due to the path dependency associated with nonlinear damage accumulation, the condition based approach can quantify the impact of the events when they occur during the operational period. This level of fidelity is required to ensure confidence when optimizing the operation of an industrial gas turbine. The drawback to this approach is the need for a digital twin, which requires significant upfront investment and expertise to create and apply, which is fundamental to ensure the confidence in the predictions. Figure 8 illustrates the fundamental differences in the approaches to predicting damage accumulation for a specific (simplified) load case.

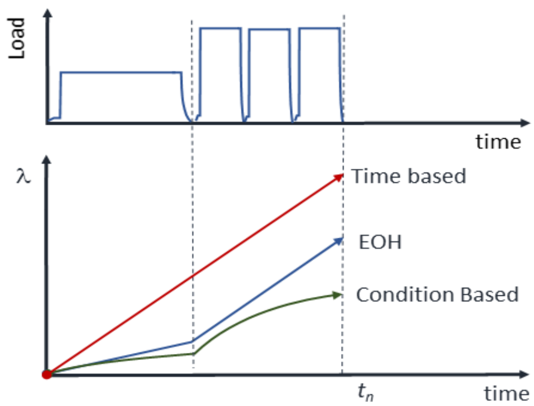

Figure 8 Illustrates the comparison of the three management approaches to a simple load case

APPLICATION OF APPROACHES TO ASSET OPTIMIZATION

As market conditions change and customers strive to extract maximum value from their equipment, it is critically important for OEMs to provide opportunities to optimize their products. The different approaches presented in this paper provide an insight into some of the ways the operation of an industrial gas turbine can be optimized. However, in order to maximize the value from the equipment, it is necessary to ensure confidence in the prediction. As discussed, overly conservative approaches may provide a coarse solution to address confidence in the prediction through the liberal application of safety factors. However, these approaches are incapable of providing a quantitative or sufficiently refined solution to truly optimize the asset. Instead, the approaches rely on experience and qualitative management techniques to allow engines to be operated outside of the initial design assumptions.

Condition based approaches provide a quantitative and refined solution to the problem of true asset optimization and provide the necessary fidelity and confidence to push the traditional boundaries of the equipment. Machine data and the applications of digital assets (twins) is key to unlocking this potential. As connectivity, data collection and the development of digital assets are becoming more widespread, the condition based approach is addressing the increasing expectation from the owners / operators to leverage technology in pursuit of maximizing value. Green et al, (ETN, 2018) provide an insight into the application of this technology through the development and deployment of digital assets. The importance of connectivity and data quality is paramount to the successful application of a condition based approach and is the owner / operators responsibility. Furthermore, not all data acquisition systems are equally as effective at collecting and processing data. A holistic approach to connectivity, data acquisition and processing such as the InSight platform is ideal and provides a balanced end to end solution that is designed to work through the whole process and provide the optimal outcome. However, as capable as these systems are, one should not overlook the importance of general conditions of operation, or the variability associated with component reuse and repair. An effective digital asset should account for environmental factors, such as the exposure to harsh environments (sulphur and salt), potentially resulting in hot corrosion (Kosieniak et al, 2012), or the potential variability and impact of remanufacturing on the material, such as multiple heat treats. As discussed in the previous section, these variations can be managed through the integration of a probabilistic framework, providing a predetermined confidence level in the prediction, i.e. 95%. Integrating this approach within a Bayesian framework would be another important step towards accounting for variability, establishing a link between model prediction and observation during overhaul and inspection. Further emphasising the need for a holistic approach to asset management and the importance of leveraging people (experience), process (maintenance and inspection) and technology (data and prediction).

To demonstrate the importance of the condition based approach, an example is provided for a high pressure, (gas producer) turbine disk. In this example, a digital asset has been created for a Titan 130 engine and applied to a specific customer and application. The process of creating, verifying and validating has been discussed previously and outlined in other publications. The digital asset creation process identified several locations for the key components within the turbine. Other locations were identified but will be omitted in order to focus on the life limiting location of the turbine rotor assembly, the 2nd stage disk. The 2nd stage turbine disk has several life limiting locations based on the active damage mechanisms within that component, namely, creep, fatigue and the potential for interaction between both mechanisms. These damage mechanisms were identified from a thorough structural integrity assessment performed as part of the digital asset creation process and is defined in detail elsewhere, (Green et al, ASME 2019). Figure 9 shows the graphical depiction of damage on the cross section of this specific digital asset from Solar Turbines Incorporated proprietary condition based lifing management system.

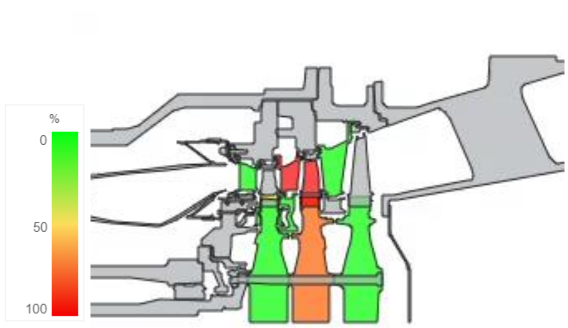

Figure 9 Depicts the damage accumulation in a hot rotor section of the turbine from the digital asset summary screen (propitiatory to Solar Turbines Incorporated)

The next step is to access and process the machine data from the full operational period. The service period under evaluation spans approximately 8 years, from 2012 to 2020. In order to accurately predict the damage accumulation for the 2nd stage disk, the machine data must be of sufficient quality and fidelity to accurately define the necessary aspects of the active damage mechanisms for the full operational period. For fatigue, this includes capturing the transient behaviour, (speeds and temperatures) of the engine during starts and shutdowns, as well as any load excursions, (full load to part load etc.). For creep, this includes continuous machine data collection during dwell periods at the different load conditions. The length of time and quantity of data needed to accomplish this is a significant challenge. Again, this challenge is discussed in detail in a paper presented by Green et al, (ETN, 2018) which covers the various aspects of data collection and processing. Needless to say, this aspect of the digital asset deployment is critically important and should not be underestimated. Figure 10 presents some elements of the machine data collected over the operational period such as rotor speed, turbine gas path temperature (T5), Compressor discharge pressure (PCD) etc.

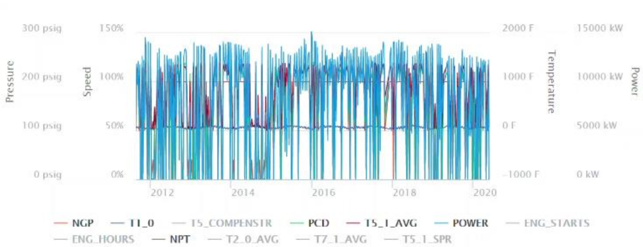

Figure 10 Shows the operational history over the 8 year service interval for the example engine

Once data has been processed and quality checked, the operational data can be used as the inputs to the damage models. In order to assess damage at the specific locations identified as part of the structural integrity assessment, the engine parameters, such as rotor speed, gas path temperatures and pressures need to be translated into load inputs and boundary conditions. For creep and fatigue this means generating metal temperatures (T_m) and stress tensors (σ_{dir}, τ_{dir}) at each location for each operational data point. Once generated these inputs can be combined with temperature dependant material models to generate the material response represented as the stress – strain hysteresis presented in figure 11.

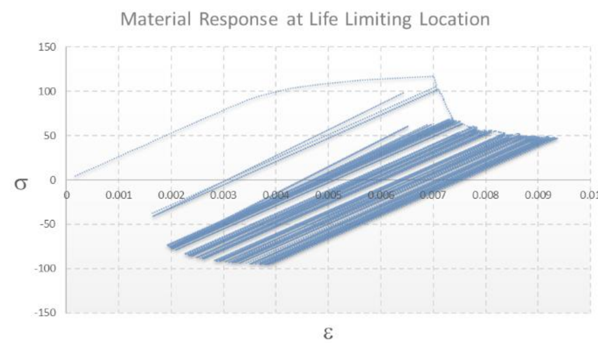

Figure 11 Shows the material response in stress & strain, for the operational profile in Figure 10

The material response curve provides an in-depth view into how each location is responding to operation over the entire service period. This provide the engineers supporting equipment health management (EHM) the first opportunity to see how that specific units' operation is impacting damage accumulation. From initial plasticity to the shakedown and stress relaxation due to creep. Interactions between creep and fatigue can be identified, such as those depicted in Figure 6, where cycles can perturb the stress relaxation during dwell periods due to creep. For this example, there is no significant interactions, however, there is both elastic damage (engine cycles) and inelastic (strain accumulation) from both plasticity during the initial engine cycle and creep due to extended periods of operation at high speeds and temperatures.

The material response is a critical step towards evaluating damage. However, stress - strain curves alone are insufficient to quantify damage, as the total damage in the material is a function of both the elastic and inelastic elements of the material response curve. As discussed in the previous sections, an appropriate damage model is required to assess the combined effects of these contributing factors. Ductility Exhaustion (Green, R., et al, US 9.200,984 B2. 2015) is one such model and when applied to the material response curve in Figure 11, yields a damage accumulation curve over the service period. Figure 12 presents the results for this example engine. The condition based results are plotted against the traditional time based approach for comparison.

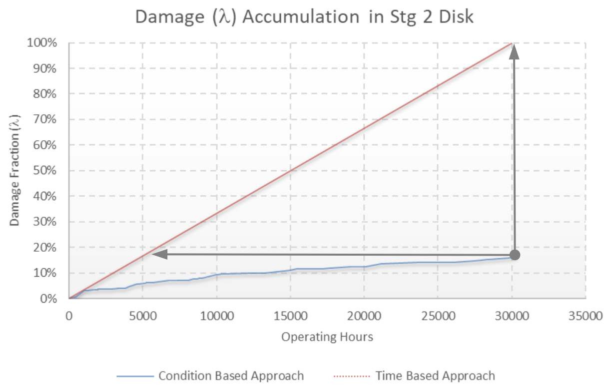

Figure 12 Compares the nonlinear damage accumulation from the condition based approach to the linear damage accumulation from the traditional time based approach

Comparing the traditional linear damage accumulation from the time based approach with the true, nonlinear path dependant damage accumulation from the condition based approach highlights the conservatism inherent in the time based approach. The equivalent hours of operation for the condition based prediction is approximately 6,000 hours, or a factor of 0.2. Therefore, 80% of the remaining useful life is still available to this component, at this specific location at the end of this service interval. This represents a substantial opportunity for increasing value either through TBO extension, increased power or both. The opportunities offered by the condition based approach are substantial and when combined with other components and damage mechanisms provide a clear path to true asset optimization.

IMPLICATIONS FOR A CHANGING ENERGY LANDSCAPE

For remote applications, turbomachinery equipment is often sized to minimize the risk of downtime, meet all possible operating conditions and provide power margin at the highest ambient temperatures. This leads to turbomachinery operating at part load conditions for significant amounts of time. While this approach offers the easiest way to assure that the equipment will meet all of the predicted operation conditions, it has drawbacks. CAPEX will be higher including the additional structure needed for heavier and larger footprint packages. Fuel consumption will be increased, larger turbines operating at lower loads will consume more fuel for the same work as smaller turbines operating closer to full load. With increased fuel consumption, there will be an increase in carbon emissions. Alternatively, turbomachinery can be sized for the majority of the operating profile. When rare operating conditions that exceed the turbomachinery's baseline performance level are required, the unit would be power boosted. Incremental damage accumulation would be calculated and assessed per the condition based model. In some cases, the cost savings are substantial.

Maintaining spinning reserve is also being challenged. Spinning reserve is the difference between the current load conditions and the maximum amount of power the turbomachinery can supply. The purpose of spinning reserve is to maintain electrical power in case of a trip of one of the turbines. For example, at the current conditions, three 5 MW turbine generators are being operated to supply 6 MW of electrical power to a remote application. One turbine generator could be shutdown and the remaining two turbines would be enough to cover the power generating requirements. However, the operator has now reduced the spinning reserve to less than one unit. In the event of a turbine generator trip, the facilities power management system would have to be activated, production equipment and non-essential loads would have to be shutdown. If the power management system failed to detect the outage quickly or did not function properly, the remote location could lose main power. One way to mitigate the risk is to allow the turbines to temporarily power boost and operate at an elevated firing temperature. This would allow time to start and load the remaining turbine generator set.

Onshore grid connected power generation turbomachinery is also being affected through changes in grid code compliance. Specifically, the need to stay connected during grid disruption events, such as under frequency and over frequency. These events are unpredictable, will vary in degree/duration, and are likely to increase as the amount of renewable power connected to the grid is increased. Power boost will likely be employed to cover the output requirements. Again, a functioning condition based model will be needed to accurately assess the accelerated damage accumulation.

With conservative equipment selections and operation of spinning reserve, time based and EoH methods have been sufficiently accurate to determine life. Today, equipment is being designed to minimize fuel consumption, decrease carbon emissions, and meet new grid code requirements; all while providing the lowest total life cycle costs. To meet these challenges more robust condition based models are needed to accurately predict component remaining useful life. Condition based modelling allows for increased operational flexibility and optimal life assessment at the widest possible operating parameters.

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