CUSTOMER ADAPTED MAINTENANCE PLAN (CAMP) – A PROCESS FOR OPTIMIZATION OF GAS TURBINE MAINTENANCE

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ABSTRACT
Maintaining high levels of availability and reliability are essential objectives for many industries, especially those that are subject to high costs due to shutdowns of critical systems, e.g. gas turbines. To utilize these systems as effectively as possible, preventive maintenance must be optimized. Determining what is optimal is, however, a multi-variable task requiring detailed knowledge about the components in the system and their different damage mechanisms. These factors have always affected the condition of the turbine and maintenance actions, but only recently has it been possible to estimate and measure them correctly for individual components during operation. In the past, it was necessary to construct maintenance intervals from the most critical component (or components), requiring the highest maintenance frequency. An additional worst-case scenario margin was also necessary, taking into account factors such as possible load variation, differences in environment (affecting e.g. turbine temperatures) and other sources of uncertainty. These uncertainties together have determined traditional maintenance planning, with maintenance packages each containing a set of maintenance activities for a set of components being predetermined and preplanned.

With the new CAMP approach, the maintenance strategy is to reach a Retirement For Cause (RFC) strategy, where components are not replaced until a potential failure has been detected. This requires measurement techniques that can monitor how the turbine is operated, prognostics capabilities that foresee maintenance needs, and test methods that can determine the state of a component during maintenance events. One important part of CAMP is therefore a prognostic tool which tells us the condition, and therefore the maintenance needs, of individual components within the gas turbine. To handle this information and efficiently make a preventive maintenance plan, software for gas turbine maintenance optimization has been developed. The software can not only calculate the most efficient point in time for a maintenance action, it can also adjust the maintenance plan to any customer's specific demands.

This paper describes the model, gathering and processing of information, risk assessment performance and the result from an optimization which groups maintenance actions as a result of customer prioritized demands. It also describes the software layout and how it is used.

INTRODUCTION
In general, downtime of a production unit due to failure of one of its components can induce high costs. Time-based preventive maintenance consisting of inspections and replacements can reduce the number of unit failures and thus lower the user's costs considerably; however, executing maintenance activities too frequently can be costly as well. The aim is therefore to determine an optimal maintenance interval, such that the total mean cost of failures and preventive maintenance is minimal. The condition of a gas turbine is mainly estimated by inspection at pre-planned intervals, typically ranging from one year and up. Hence, gas turbine maintenance planning consists of maintenance packages, each containing a set of maintenance activities for a given set of components.

Gas turbine preventive maintenance intervals have traditionally been decided by Equivalent Operating Hours, EOH, or Equivalent Operating Cycles, EOC, or a combination of both. A gas turbine accumulates EOH/EOC depending on e.g. fuel type, load, trips etc. The major drawback with this approach is that all components within the gas turbine theoretically accumulate damage even though in some cases no
damage has actually been accumulated to a component.

With a growing emphasis on life cycle cost reduction for capital equipment such as gas turbines, equipment operators are increasingly investigating potential for cost reductions. To minimize life cycle costs and maximize earnings, one of the most important ways, according to Siemens philosophy, is to optimize maintenance according to a customer’s specific condition. Achieving the optimal maintenance plan, which minimizes the total cost, depends on the availability of diagnostics, prognostics and maintenance planning technologies.

Condition Based Maintenance is a term for methods and methodology that, based on the actual condition and predicted future use, in theory allows maintenance to be performed at the best possible date for each component. Any data that is used to assess equipment performance and operating health is termed CBM.

CBM tasks are normally applied to components of a system that do not fail instantaneously but fail over a period of time and then give some early indication of an impending failure. The early indication of failure enables the user to avoid the consequences of an unexpected breakdown. Early signs can be detected by the use of diagnostic equipment and/or by maintenance inspections. The frequency of any inspection schedule depends on the time between the early signs of failure and the point at which failure occurs. With this approach, all major parameters are considered in order to maximize accuracy. For this reason, detailed information should be available.

However, merely having diagnostics and/or prognostics is not enough to derive full or even most benefits from CBM. It has been stated that in order to maximize the benefits from CBM for the enterprise, it is as important to focus on the aftermarket supply chain – i.e. the back-end of the process – as it is to develop better data gathering, diagnostic and prognostic techniques. Further, it is shown that optimizing the value chain results in lower costs and higher availability. Providers of maintenance service, increasingly the Original Equipment Manufacturer (OEM), stand to gain as well. It has also been shown that equipment operators are striving at increasingly using condition based maintenance instead of, or in addition to, scheduled maintenance as a way to reduce lifetime equipment operating costs.

To cope with this, Siemens Industrial Turbomachinery defines a fully implemented CBM strategy as a process consisting of prognostics, diagnostics and optimization tools. All pieces are equally essential; otherwise it will not be possible to fully benefit from a CBM strategy. We call this process CAMP, Customer Adapted Maintenance Plan.

The added complexity of optimization for the very dynamic maintenance situation, which is the result of CAMP, may therefore be perceived as a problem. But this is exactly where the real benefits of CAMP lies – in the ability to precisely adjust the maintenance timing and level to the actual condition of the turbine and its components. What really matters to gas turbine owners are factors such as full maintenance costs, or the total cost per e.g. kilowatt. In response to this, OEM’s offering maintenance contracts must fill the needs for optimization of lifecycle costs by leveraging core competencies and efficiencies of scale to provide the service. Developing accurate and comprehensive customer knowledge is crucial to reducing costs because solutions engineered for one customer can then be adapted to the specific needs of other customers.

Diagnostics is the ability to detect an increased risk for a failure and propose action in order to prevent a failure of components and consequential damages. There are many different monitoring techniques on the market, from vibration monitoring to intelligent solutions such as artificial neural networks. However, these techniques will not provide enough information to adapt maintenance plans to customer’s specific conditions, only to identify anything which deviates from normal operation characteristics.

A prognostic tool is used to predict the future wear of a component, given component properties, operation profile and ambient condition. A damage algorithm is used for critical damage location on components subject to preventive maintenance. A prognostic tool must therefore not only calculate consumed lifetime, but also administer a lot of data e.g. material properties, measured and calculated values in the hot path section of the gas turbine and combine this into a prognosis.

As a consequence of the more exact knowledge of the maintenance needs of the gas turbine, maintenance intervals no longer remain fixed, but instead vary depending on the condition of several components and a variety of other factors e.g. actual load profile, quality of fuel, ambient temperature, particle levels etc. This information will be combined with the operator’s opportunities and demands for the maintenance to be carried out as effectively as possible. Thus, a CBM business model will ensure that the potential for short-term profits will be evaluated in an overriding life cycle cost perspective.

To manage all the information in our CBM strategy, a Preventive Maintenance optimization tool called PM-opt has been developed. PM-opt will plan preventive maintenance for any complex technical system and maximize earnings for a system operator. This is done by the use of an advanced prognosis process and input from an operator regarding operation profile, ambient conditions and financial data such as production value and standstill costs. This information will be processed in PM-opt, generating an optimized preventive maintenance schedule adapted to an operation-unique situation and hence maximizing profit. The process is finally supported by an advanced diagnostic tool to further increase reliability and availability.

The goal is to provide operating conditions that will increase availability with predictable scheduled maintenance, based on condition monitoring assessment with little or no downtime during deployments. Any changes in e.g. operation profile will instantly affect the preventive maintenance. Also, if
an unplanned opportunity occurs, maintenance can be re-scheduled if it is proved profitable to use this ‘slot’. PM-opt can deal with these situations and re-optimize maintenance if this is proven financially justifiable for an operator of a gas turbine. The objective of the Siemens Industrial Turbomachinery CAMP approach is to maximize profit for operators of gas turbines.

NOMENCLATURE
CAMP – Customer Adapted Maintenance Plan
RFC – Retirement For Cause
EOC – Equivalent Operating Cycles
EOH – Equivalent Operating Hours
OEM – Original Equipment Manufacturer
CBM – Condition Based Maintenance
PM-opt – Preventive Maintenance Optimizer
LPT – Lifetime Prediction Tool
MUPP – Maximum Utilization of Parts Process

GAS TURBINE MAINTENANCE PLANNING
For gas turbines, maintenance planning is usually done many months in advance due to the user’s cost associated with a period of turbine inactivity. The date and duration of a maintenance period are determined in advance to coincide where possible with other scheduled stops, such as plant shutdowns and vacations. With a CAMP approach flexibility depends on a lot of different factors such as risk willingness, condition of components, value of production and future operation profile. The major advantage for a customer of a CAMP agreement is that the maintenance plan can be adapted to his specific demands and needs, and at the same time he will gain transparency regarding the possible consequences of different approaches. Also, each component will be utilized as efficiently as possible, which reduces downtime and costs and increases the potential earnings due to an increased number of operating hours.

CBM and Gas Turbines
The benefits of utilizing CBM over a time-based preventive approach to reduce lifecycle cost have been well documented over the years. However, CBM has become a catchall term for any type of health monitoring [4]. A majority of papers written on CBM or Health Management of Machines focuses on the areas of diagnostics and prognostics. There are many techniques and emerging technologies that are making engine monitoring more complete and informative. One such major focus is in sensors technology to enable a much greater range of data. Basic parameter monitoring can and does provide valuable information on the performance of an engine [5]. Through intelligent processing, and integration with other parameters, valuable information can be acquired including actual life consumed, life remaining, and the condition of the gas turbine relating to its operation profile and ambient conditions.

These approaches mean dealing with a large amount of data, and for this reason, statistical approaches are becoming popular tools for life management [6]. Applications include calculating the risk involved in extending the life of components. Retirement For Cause (RFC) is an approach that allows each component in an engine to be used for the full extent of its safe life [7]. Statistical approaches like Weibull analysis are popular in the world of industrial turbines. OEM’s usually have databases on the number of parts retired from service as a function of operating parameters. Theses samples can, however, be quite small and the root cause not properly identified.

The difficulty is to use these techniques in order to maximize a customer’s earnings and hence increase competitiveness on a market. To be able to achieve this, the data from diagnostic and prognostic tools must be sensitively handled in combination with a customer’s business system. Our solution is to use our PM-opt tool, using advanced diagnostics and prognostics tools to estimate when in the future a component in an engine must be maintained. This means planning maintenance from an ‘item’ point of view. An item can consists of a single component, e.g. a blade or a guide vane, or a set of components together creating an item, or a regulatory demand of e.g. emissions-measuring calibration. The tool described in this paper can handle this information and use an operator’s unique operation characteristic to create an optimal maintenance plan adapted to his needs.

Maintenance optimization
One of the major questions, if not the most important one, to be answered by persons responsible for the maintenance management of gas turbines, is when to do a maintenance action: “The maintenance action is due at a certain date – can we postpone it?” This optimization problem clearly belongs to the advanced maintenance sphere. This and other questions regarding optimal or near-optimal decision making is becoming more and more important together with an increased focus on cost minimization and profitability within the gas turbine sector. The type of problem dealt with is however of a very complex nature, and the question is therefore difficult to answer simply. To handle the complexity of the problem, we have used combinatorial optimization methods which can handle a wide variety of side constraints and different costs.

Equipment such as gas turbine components (discs, combustion chambers, compressors, power turbines and the like) are operated under varying conditions. Appropriate maintenance of the equipment is required to avoid overall loss of power output resulting in costly repairs and non-payment due to equipment failure. Because frequent preventive maintenance is costly, optimal or near-optimal maintenance planning has been a primary development interest for Siemens. Although there are some reliability prediction techniques for mechanical equipment based on various planned maintenance procedures, these methods have been difficult to apply on CBM for gas turbines in industrial applications. For this reason, maintenance timing has been determined heuristically, using
experience of technical expertise in combination with limited calculations and tests to estimate equipment lifetime. The major factors behind this undesirable situation are unavailability of sufficient field data, involvement of many physical parameters, complexity of existing models, and difficulty of determining model parameters by using actual data. The ability to determine the maintenance timing for each component of the gas turbine is one of the major obstacles on the road to optimal use of gas turbine equipment.

A well known fact is that components in a gas turbine face different wear, depending on parameters such as environment, load, events, fuel type etc. This means that two identical gas turbines with different operators can present significant differences in wear. In order to make an optimization, every component in a gas turbine must be monitored and the accumulated equivalent operating hours (EOH) and equivalent operating cycles (EOC) must be considered. In addition, predictions based on an estimate of the expected future wear should be available in order to compute expected maintenance deadlines.

In the optimization, a clear distinction must be made between normal components and an Item. An Item is a component whose condition can be measured more accurately than by simply computing accumulated EOH and/or EOC. As an example, the wear of a single guide vane or a single blade can be accurately measured during an inspection. Because we can expect the wear of components of equal type to be somewhat similar, we usually group several components into a set, represented by a single CBM component. Following the example above, we could have a single Item for all guide vanes in the first stage of the gas turbine.

The residual lifetime of the Item is represented by the most worn component in this set. As long as operation is normal and a component is not subjected to damage (e.g. due to foreign objects or deviation in temperature profile causing uneven wear) all components in a set are replaced at the same time. However, if components face unequal wear, the replacement of such components must be done with great care. Failure to do this properly may result in sub-optimization, causing increased cost in the future for an operator due to higher maintenance frequency as a function of uneven component wear. This is avoided by the use of a highly detailed components database with component traceability, ensuring an effective replacement schedule throughout the gas turbine’s lifetime.

Example: If we view the result from a prognostic tool, and use seven different Items called A-G, the point in time for each Item’s maintenance activity is shown in Figure 1.

![Figure 1: Gas turbine Item replacement scheme using fictional replacement intervals in the PM-opt software. The upper view shows the optimal replacement plan with regard to Item utilization only.](image1)

These are the optimal points in time to perform replacement or inspection if an operator wants to utilize the components as efficiently as possible. However, due to the high cost associated with a shutdown, this approach is unacceptable. The Items must be co-allocated into fewer but larger “maintenance packages” in order to minimize downtime and overheads associated with maintenance. Still, the maximum allowed Item lifetimes are important inputs to the optimizer. However, in order to avoid sub-optimization we must ensure that all significant costs are taken into account. Thus, supplementary information must be added.

Figure 2 shows how future maintenance needs are planned and the latest point in time for when an action must be carried out. The objective of the problem is to decide at which point of time all actions should be carried out in order to minimize the cost of the plan. In other words, the opportunities, or planned periods where maintenance is to be carried out, must be filled with appropriate activities, thus forming maintenance packages such as those shown in Figure 3.

![Figure 2: Gas turbine maintenance planning.](image2)

Figure 2 shows gas turbine Items with lifetimes and maintenance opportunities in calendar time. The optimization task is to decide which turbine Items should be maintained at
which opportunity, while at the same time minimizing global cost. Each maintenance opportunity has a maximum stop time and a specification of downtime cost for maintenance at that opportunity.

Figure 3: One set of maintenance packages and their respective opportunities.

In figure 3 are the activities allocated to a single opportunity forms a maintenance package. The remaining lifetime of the Items corresponds to the distance between the square (planned maintenance) and the black dot (maintenance deadline).

The maintenance optimization will be performed dynamically with a predetermined frequency, e.g. once every month, at which time information on the monitored and calculated condition of the different damage locations on each component will be transferred to the optimizer. If each Item were maintained at the individually optimal point, the availability would be unacceptably low. So, the information given tells when a maintenance activity will be carried out, with the planning of the activities grouped in an optimal way, as shown in Figure 4.

As a note on the problem complexity from an optimization perspective, the planning problem can be seen as a much generalized and more complicated form of bin-packing [8,9]. This problem is in turn a well-known hard optimization problem, where the optimization time in practice is often proportional to an exponential function of the problem size. However, by using Items and clever algorithms, the problem complexity can be reduced to a manageable size.

The optimization algorithm used is divided into two stages. The first stage applies a depth-first branch-and-bound algorithm [11] augmented with a heuristic to find the best possible maintenance plan. On top of this, an iterative widening technique called Limited Discrepancy Search [10] is used to find better maintenance plans fast. In short, the first stage selects individual maintenance activities in turn, ordered by increasing deadline. The algorithm then tries to allocate the selected maintenance activity to each possible opportunity, and evaluates the results of doing this in combination with the previously committed allocations. The possible opportunities are then sorted according to increasing cost, and the best one is committed for further evaluation. The search then proceeds by selecting the next activity in turn for allocation. If at any instant an inconsistency is detected, the search backtracks to the previous choice, and the next best opportunity is tried instead. At each allocation choice, at most k opportunities are evaluated; whenever no opportunities exist, the search backtracks. In our experiments, we have found that iteratively increasing k from 0 to 2, resolving the problem for each k, gives good performance and quickly returns feasible improving solutions.

When all activities have been allocated to opportunities, the cost of the resulting plan can be established, and if the generated plan is better than the best one found so far, it is saved for future reference. The search then backtracks in order to find better plans. Also, a simple lower bound of the cost for an incomplete plan is computed and used to backtrack as soon as the lower bound is higher than the cost of the best plan found so far.

The second stage of the algorithm is similar to the first one, but a breadth-first technique similar to A* search [11] is used instead of a depth-first strategy. In this stage, a set of partial plans (“nodes”) are kept ordered according to a heuristic value, which is the sum of the partial plan cost and the lower bound for the unallocated maintenance activities. The node with the lowest heuristic value is selected first, and is expanded into several new nodes, which are inserted into the set. The expansion is done by splitting the set of possible opportunities for an activity into two sets, yielding two new nodes each having one part of the opportunity set for the activity.

Since planning an activity at an early point in time incurs a cost in lifetime loss for that Item, the optimizer favors late maintenance over early. However, since downtime costs are also taken into consideration, it may be even more favorable to place an activity at an early opportunity, if that date already contains other maintenance activities (in which case the

Optimization problem and difficulty
Component life assessment

What maintenance is all about is to increase the life of the equipment by planned and unplanned activities that verify component functionality and detect faults preferably before they occur. A typical scenario is seen in Figure V: At each maintenance event the component life is assessed and, depending on the result, new optimistic and pessimistic curves are drawn. As can be seen in the figure, there is always an uncertainty in the assessment of the component’s state. This uncertainty is strongly influenced by the test method used.

![Figure 5: Component maintenance activities and life extension](Image)

The determination of the optimistic and pessimistic curves is based upon many assumptions. Often there has to be some level of conservatism in judging lifetimes. This may lead to situations where the actual failure probabilities of the components in question are magnitudes below their target values. In theory this is good for the equipment safety, but will result in premature replacement of equipment, and deterioration in plant economy. Further, due to the small but not negligible probability of manufacturing flaws in newly installed components, premature replacement may actually increase the risk of equipment failure. Optimum life utilization with best cost–risk assessment will be possible only if life estimates are realistic from the beginning, or if the life estimates can be improved with time.

**Prognostics**

When creating and managing a customer adapted maintenance plan, a lifetime prediction tool (LPT) is essential. The LPT will keep track of a number of damage locations for each component in a gas turbine, e.g. creep, fatigue, erosion, oxidation and corrosion.

At sufficiently high temperatures – and under certain circumstances at low temperatures also - metal alloys will deform with time when subjected to external loads. This phenomenon has two consequences: firstly, the inelastic deformation will cause the component's shape to change. For rotating blades this may result in rotor – stator interaction and loss of integrity of the component. Under certain conditions it will also lead to waist formation and rupture. This may be common in creep tests under standard test conditions.

Secondly, creep load may cause the formation of creep cavities in the component, preferably but not exclusively along grain boundaries. With time, the cavities will join together and form so-called creep cracks that may result in creep rupture. It is believed that creep deformation is an issue of at least the same magnitude as creep damage since most materials can sustain enough creep deformation without cavity formation to allow the closure of standard rotor – stator clearances.

Fatigue damage is caused by start-ups and shutdowns. The rate of damage accumulation is strongly related to the load and unload profiles of the gas turbine. Basically, fatigue damage develops in two stages: crack initiation and propagation. The duration of both stages depends on the amplitude of the cyclic stress. These fatigue mechanisms, especially crack propagation, may interact with other types of degradation, dependent on temperature, environment etc.

Damage resulting from erosion is a reduction in thickness of components due to the mechanical effect of abrasive particles or water droplets. The most frequent cases of erosion are observable on blades and guide vanes due to gas (air or combustion) mixed with particles. This erosion depends on two factors: gas velocity and quantity of particles. Generalized, corrosion affects any surface exposed to an aggressive liquid. Eventually, metal dissolution can develop when a protective layer is eliminated.

The initiation of corrosion originates mostly from impurities entering the gas turbine with the fuel, water and/or air flows. Corrosion mechanisms can appear in many different forms. Which mechanism will appear depends on factors such as the metal composition of the different components and the number of impurities present. Conditions, such as temperature, vary a lot between different parts of a gas turbine. So the corrosion mechanism also differs, for example, between the...
compressor and turbine. The compressor and air intake system are subject to low-temperature corrosion, whereas the turbine is subject to hot corrosion.

Oxidation is the chemical reaction between oxygen in air or, more typically, combustion gas and alloy elements in the component surfaces. Oxidation has two detrimental effects on components: Loss of metal due to the formation of surface oxide layers that will fall off, thereby reducing component wall thickness, and the removal of certain alloy elements from the base metal through diffusion to the surface oxidation areas. The rate of damage accumulation is mainly dependent on temperature and material, and can be reduced by the application of surface coatings.

The prognostic tool calculates the residual lifetime depending on a customer’s operation profile, environmental conditions and actual gas turbine data. The prognostics tool is an advanced EOH/EOC calculator keeping track of every damage location on the gas turbine’s components. When a certain damage location reaches a predetermined limit, either an inspection or a replacement is necessary (see Figure 6).

![Figure 6: EOH/EOC accumulator.](image)

As operation commences EOH/EOC is accumulated on each damage location. The location with the highest amount of accumulated damage represents the condition of the components and, hence, the CBM component. The reaction time is the time needed for Siemens to plan and execute a maintenance task; this varies with different CBM components.

The data from site, as described earlier, comes from a data acquisition system. The collected data is transferred to a central database via a remote connection on a regular basis. The data is linked to the prognostics tool and the residual lifetime for each component is calculated.

The operator’s specific characteristics are used, in combination with knowledge about and wear of components, to customize an optimal maintenance plan for his turbine. The maintenance plan will be dynamically updated in order to increase the precision in the prediction of the point in time, at which a planned maintenance action must be performed (see Figure 7).

![Figure 7: Point in time for planned maintenance action.](image)

This figure describes the dynamic maintenance plan and how information is gathered during operation to more precisely estimate the point in time for a maintenance action. Also, the risk associated with postponing an action can be calculated.

**Maximum utilization of parts process**

Component lifetime is a phenomenon that is often mentioned but rarely given a detailed definition. One definition used is: “The lifetime of a component is the time during which it fulfils its design purpose adequately without exposing humans, surrounding equipment or the environment to unacceptable risks”. This question is becoming increasingly important when Retirement for cause (RFC) or Condition Based Maintenance (CBM) strategies are implemented. As mentioned, Retirement for cause is a strategy that aims at replacing components only when detectable, non-reversible damage has occurred, and is typically used for extremely expensive components with relatively uncomplicated damage patterns, like rotors.

In general there are two ways to determine the amount of damage a gas turbine component has been subjected to – calculations and examination of components exposed to service. Optimum results should be obtained by using calculations as a basis and continuously review/modify their interpretation and the underlying damage models using best available experience. This Siemens process is called Maximum Utilization of Parts Process (MUPP) – a process for systematic testing of used components: How process data can be turned into modifications to a gas turbine’s maintenance plan with same or decreased risks, and the implications for equipment operator as well as maintenance provider.

**Component set status assessment and relative positioning**

By extracting sample components during inspections, the status of one set of components, as compared to standard lifetimes and to other sets of components operating under the same conditions, can be determined. This means that the benefits of the procedure indicated in Figure V are used. However, usually the gas turbine is disassembled at least once before most com-
ponents are scrapped, allowing access to the components for
detailed status assessment. Therefore, by picking sample
components for destructive testing even before reaching their
expected end of life, valuable knowledge about their actual
service conditions can be gained and their service life can be
extended accordingly. This also means that even moderate
lifetime improvements become much more valuable to the end
user. If the end user has periods of time where the engine is
idle, or operates with a very small downtime cost, it may even
be beneficial – from a life utilization point of view – to shut
down the engine in order to extract components for
examination. This has to be judged from case to case.

Component life extension
As a gas turbine accumulates operation hours it will be possible
 to see some patterns during inspections and overhauls. If the
components in one stage “always” look notably good this
should mean that there is something in the conditions at the site
that is lenient to the components. This means that when adding
a new set of components, the expectation on their actual life
could be increased somewhat, and the “halfway” inspection can
be adjusted towards the half-life that should be expected in this
specific gas turbine. It should not be recommended, however,
to postpone the first inspection beyond the “safe life” limit of
the component, since there is always a possibility that
conditions may have changed to the worse. Additional safety
margins may be desired dependent on the circumstances.

Engine change monitoring and life monitoring
If all turbine components in all stages, as well as the combustor
components, look notably good, this should say something
about the actual operation conditions of the engine as a whole.
This means that not only the component characteristics could
be adjusted, but the engine characteristics also. If the possible
sources of deviations in the engine calculations, model is
known, it is possible to adjust the model, using well defined
 calibration parameters for each known uncertainty, until it
agrees sufficiently well with the actual findings. The outcome
is an engine model that is tailored to the actual site conditions
and that should be able to predict the actual state of the engine
much more accurately than the unadjusted generic model. This
has three very important consequences: a) Before components
are inspected, the engine model and experience should allow a
fairly accurate prediction of the state of the component; b) If
the component does not look as expected, the engine model
should be able to predict how this influences all other
components in the engine; and c) This means, that based upon
inspection results from one component, it is actually possible to
draw conclusions from one component about all other
components, and adapt the maintenance strategies for all of
them accordingly. In practice this means that when the model is
calibrated, the 1st cooled and the 1st uncooled stage blades can
be used to monitor changes in the engine state, and form the
basis for long-term fault detection and trend analysis also for
individual components. In conjunction with advanced hot gas
inspections this system should allow successive optimization of
maintenance intervals for hot gas path components with
increased reliability and the same availability as today, or
higher.

CONCLUSIONS
Siemens’ approach to CBM is a maintenance philosophy and
methodology that will allow us to meet high demands from the
market regarding lifecycle profit. To be successful requires
advanced technologies and a close relationship between
maintenance supplier and operator. Full and adequate
implementation will require CBM-enabling of health
monitoring and assessment of systems having diagnostic,
prognostic and optimization. The CAMP approach requires on-
site system with the possibility to gather data remote use
communication technologies in order to transmit truly real time
data between a site and a logistic centre with experienced OEM
personnel available. This will enable more adequate trending
and adequate projection analyses on the life cycle management.

Our approach not only uses advances diagnostic and
prognostic tools, we can also use the information to create
optimized maintenance plans adapted to a customer’s operation
profile, technical specifics and financial situation. This
approach is built on our core competence in understanding the
diagnostic and prognostics of engine health and is used as input
into PM-opt software in order to provide a way to maximize
life cycle profit of gas turbine ownership.

The goal of a maintenance strategy should be to reach a
Retirement for cause (RFC) condition, where components are
not replaced until a potential failure has been detected. Further,
the inspection interval should be large enough to allow spare
parts to be ordered and delivered during the time between
failure detection and failure, with sufficient safety margins.
This requires measurement techniques that can monitor how
the turbine is operated, prognostic capabilities that foresee
maintenance needs, and test methods that can determine the
state of a component during maintenance events. We can also
show how e.g. changes in operation profile will affect the
future maintenance needs. If an operator changes, for example,
from a base load application to a peak load application, we can
re-calculate lifetime of critical components and create a new
maintenance plan, building on operation history and future
operation profile. The operator will be given new flexibility in
terms of planning his preventive maintenance. With a CAMP
contract, each critical component within the gas turbine is
condition-monitored and any influences from, for instance, a
changed operation profile or from unforeseen events will result
in a new, optimized maintenance plan.

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