Development of Diagnostics & Prognostics for Condition-Based Decision Support

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ABSTRACT

The market for civil and military aerospace applications shows an increasing demand for service-based contracting ("Performance Based Contracting" - PBC). These contractual-concepts are based on guaranteed performance indicators over a fixed period, enabling a share of the financial risk between the system provider and the operator. The realization of efficient condition monitoring capabilities and reliable prognostics for prediction of spares and personnel demands has been identified as one key enabling factor for a successful implementation of PBC-concepts. To ensure an optimal incorporation of the diagnostic & prognostic functions needed for this purpose, the integration has to be considered as a standard design task during the development and certification phase, rising the need to adapt existing development processes. This adaption includes the extension of certification guidelines, definition of dedicated requirements and realization of innovative verification strategies. During the last years Airbus Defence & Space was working on the definition of a development process for integration of an innovative health management strategy into new aircraft systems to support condition-based operations. Following a summary of condition monitoring and prognostic techniques, selected requirements and guidelines for development of diagnostic & prognostic functions will be presented and discussed.

1. INTRODUCTION

For the civil aerospace sector, the highly competitive situation and simultaneously continuously growing market are motivating factors for the development of new and attractive business models. The global competition has also an increasing relevance for the military sector but the only annually available funding of the governmental customers is an additional regulating factor. To realize new development programs under these conditions and in despite of more and more limited budgets, future activities have to ensure minimized and predictable costs for development and operation & support. PBC-concepts are one possible solution to reduce the financial and operational risk for the operator, while providing technical sophisticated systems. The main attributes of such PBC-concepts are therefore defined through cost efficiency and operational performance, whereas the respective contents of the contract are application specific.

Beside the system design itself, the strategy for maintenance and on-demand provisioning of resources is one of the fundamental aspects to control operation & support costs and system availability (Lee et. al, 2008). Hence provisioning of spare parts and qualified personnel at the right place and the right time without any oversupply to avoid excessive costs for personnel, production and logistics, is one major challenge for the successful implementation of PBC-concepts (Reimann et. al, 2009). This demand can be fostered through an efficient health management system with failure prognosis capabilities (Jazouli & Sandborn, 2011 and Wilmering & Ramesh, 2004). A maximum capitalization of the information provided by the health management system can only be achieved with an integrated solution for condition-based maintenance and mission management. An appropriate development process is a mandatory prerequisite to integrate these capabilities into a new system design. The establishment of such a process for the development and certification of integrated diagnostic & prognostic functions to enable condition-based decision-making is still an ongoing task. The majority of publications in the field of Prognostics & Health Management (PHM) are discussing modelling, simulation and algorithms for various applications. Only very few authors have discussed the topic of validation & verification as part of a development process to an extent that can be applied to aerospace applications (Kacprzynski et. al, 2004, Leao et. al, 2008 and Saxena et. al, 2010). The aim of this paper is to detail an approach that allows for inclusion and verification of design requirements for PHM functions into the development process for new or legacy systems. After an introduction to the principles of Condition-Based Operations a review of the current status within the emerging field of diagnostics & prognostics will be given. According to the main aim of the paper, the status reviews are followed by the derivation of appropriate design requirements and established validation & verification strategies.

2. DESIGN ELEMENTS OF CONDITION-BASED OPERATIONS

The main elements of condition-based operations as considered by Airbus Defence & Space are depicted in Figure 1:

1. On-board health management functions and data transmission.
2. Evaluation of health management information using prognostic functions to enable predictive decision support.
3. Decision Support including evaluation of different options for dynamic mission and maintenance scheduling.
4. Performance Based Logistics for an optimized resource and supply chain management.
5. Certification of condition-based decision-making and configuration control to ensure continued airworthiness.

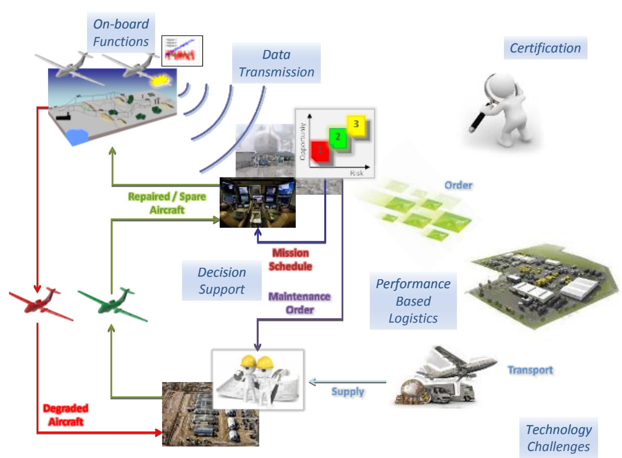

Figure 1. Design elements of condition-based operations

The main technology challenges can be seen in the development of on-board monitoring functions, regularizations for data security, integration of off-board functions for predictive maintenance and mission management and the on-demand strategy for supplier and logistic supply chain management. Apart from the technology maturation, all design elements need to be developed under the guidelines of the respective authorities to ensure certifiability for new products and continued airworthiness for upgrades of legacy systems. The field of diagnostics & prognostics is one important contributor for the realization of condition-based operations, as the information from the health management system is one of the main inputs to dynamically optimize maintenance and mission planning.

As for the development of other on-board and off-board functions, diagnostics & prognostics also require the definition of verifiable design requirements. Airbus Defence & Space has developed a virtual framework to support the validation & verification of design requirements for a health management system (Mikat et. al, 2012). The model described in (Mikat et. al, 2012) has been validated against a certified environment and the requirements and concepts described in this paper are now an integral part of the framework to support the development of diagnostic & prognostic functions. The implementation is done as shown in Figure 2. The contents of this paper are discussing selected requirements and concepts from the elements marked with "Requirements Application".

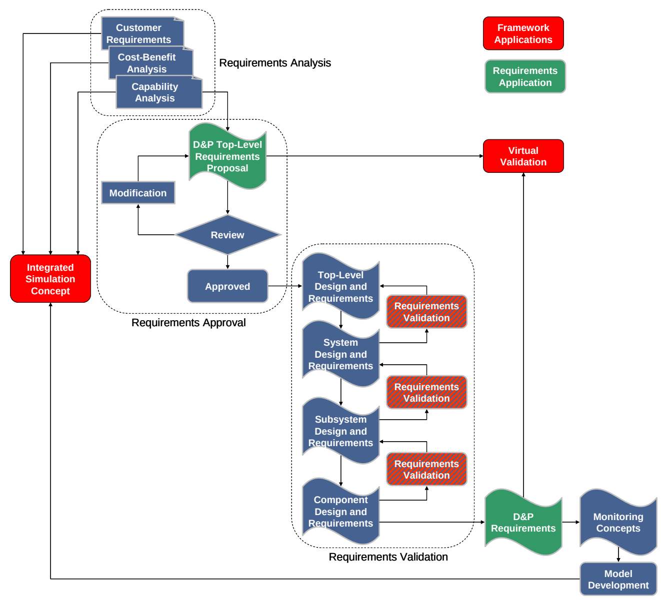

Figure 2. Development process for diagnostic & prognostic functions

The following chapters will focus on a status review of condition monitoring in general and prognostics as an integral part for condition-based operations. The main requirements for definition of diagnostic & prognostic functions that can be applied to any design task from this field are presented and discussed. The discussion includes the implementation of a general approach to evaluate the performance of prognostic concepts.

2.1. Condition Monitoring

Today's condition monitoring systems for aircraft applications are based on a combination of Built-In-Tests (BIT) and health monitoring systems (Srivastra, 2009).

Therefore dedicated instrumentations and data analysis concepts are considered during the system design stage. The BIT shall ensure that all relevant failure modes become evident to the flight operator. Different classes of BITs ("Power-Up BIT" during component or system start, "Continuous BIT" during continuous operation and "Initiated BIT" during specific operating conditions) are considered and evaluated according to a predefined monitoring concept. The results from the BIT monitors are compared with specified thresholds, to decide whether the respective function can be supported as required. Repeatability and reliability of the BIT is ensured by the fixed test procedures and thresholds for unacceptable conditions that have been defined and verified during component and system qualification. The evaluation of BIT information is a mandatory input to continuously verify the airworthiness of the operating system.

In addition to BITs, selected parameters and conditions are subject to a continuous monitoring and assessment of the remaining margin to predefined damage or performance thresholds (COndition Monitoring function - COM). Examples are the "Usage Monitoring" for structural parts (Hunt & Hebden, 1998) or "Engine Trend Monitoring" for jet engines (Kühl & Pakszies, 2011).

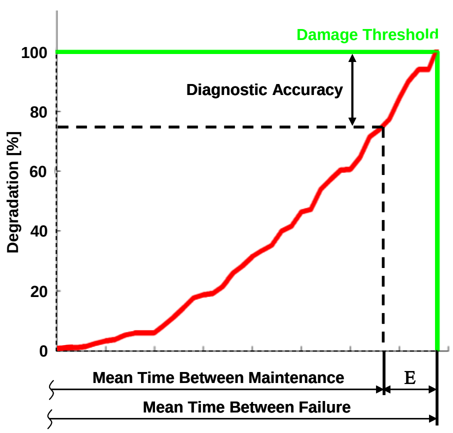

Figure 3. Condition Monitoring concepts and impact on the operating system

The main difference between these two approaches can be seen in the high reliability of the BIT to distinguish between two conditions (operative or non-operative) and the capability of the COM to continuously quantify changes in the operating conditions before a failure or malfunction occurs. The impact of BIT and COM on maintenance intervals and the useful life consumption is shown in Figure 3. The BIT would indicate the failure when the predefined threshold is exceeded, causing an operational interruption due to a failure event, while the COM avoids the failure and maximise the availability by the initiation of a preventive maintenance action. The waste of useful life □ can be minimized with increasing accuracy of the diagnostic & prognostic function. For real world applications E will always be greater than zero, affecting the useful life consumption of the monitored equipment adversely but avoiding unacceptable degradation levels. Therefore the design aim for COM functions should be to maximize the component utilization (which is equivalent to minimizing □), while also ensuring a simple and robust monitoring concept with a minimum impact on the system design and operation.

2.1.1. Classification of Condition Monitoring

In general condition monitoring techniques can be classified into data-driven and model-based approaches (Venkat et. al Part I, 2003 and Schaab, 2010):

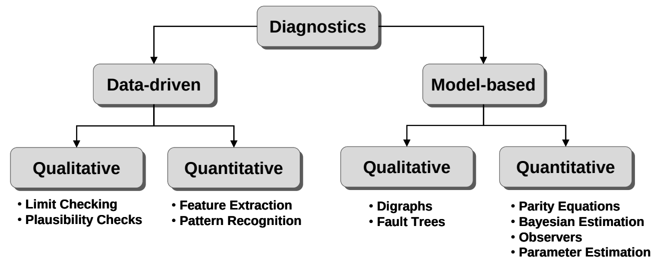

Figure 4. Classification of diagnostic approaches

The class of qualitative data-driven approaches is robust and easy to implement. Limit checking and plausibility checks are used for numerous industrial applications (Münchhof, 2006). These concepts require usually no complex algorithms and the main effort can be seen in the derivation of reasonable thresholds to decide whether the monitored function is satisfying its requirements or not.

The quantitative methods are utilizing extensive datasets with and without failure signatures to identify whether the observed process has a nominal or faulty behaviour. The health assessment is done based on pattern recognition algorithms, by analyzing selected features from the collected data (Venkat et. al Part III, 2003). The concept for feature generation is very problem specific and needs to ensure that the fault signature is evident to the algorithms for pattern recognition. Commonly used classification methods include but are not limited to Bayesian Decision Theory (Pipe, K., 2003), Neural Networks (Ypma, 2001) and Support Vector Machines (Schaab, Harrington & Klingauf, 2007).

Model-based approaches are utilizing a logical or mathematical description of the monitored process to compare the expected behaviour with actual measurements. The results of this comparison are used to derive estimates for the actual health status.

Qualitative models are an abstracted version of the underlying process and are used if no detailed physical modeling is needed or the complexity of the process does prohibit the model development (Venkat et. al, Part II, 2003). One example are logical graphs, which include information about the cause-effect relationship of failure modes that can be used for fault detection and isolation (Chung-Chien & Cheng-Ching, 1990).

Quantitative model-based methods are based on a detailed mathematical model, which represents a virtual redundancy of the monitored process. The models are used to derive a residual, which describes in case of a fault occurrence the difference between the nominal and faulty behaviour. The residual is then used to isolate and quantify deteriorations or malfunctions of the process. Various examples like parity equations (Isermann, 2006), recursive Bayesian estimation (Crepin & Kreß, 2000) or parameter estimations techniques (Isermann, 1992) have been discussed.

Following the above given definition for BITs and COM, the BIT can usually be seen in the context of qualitative methods, enabling detection and isolation of an already occurred failure. The capability to detect, isolate and quantify a deviation from the nominal behaviour requires a deeper analysis of the monitored process and therefore COM approaches would be expected to come from the field of quantitative methods.

2.1.2. Development of Condition Monitoring

The development of the above mentioned capabilities needs the establishment of design requirements for validation & verification of the diagnostic performance. To support this task, the following qualitative requirements have been identified as relevant for the development of Diagnostic Functions (DF) for all COM monitored items:

- The DF shall indicate the minimum detectable damage size.
- The DF shall quantify the remaining margin until the damage size exceeds a maximum allowable limit.
- The DF shall enable root cause isolation on component level.
- The DF shall provide the confidence level of damage size quantification.
- Each DF shall be provided with a value for the critical damage size of the monitored feature.

Once the requirements for DFs have been defined, the particular monitoring concepts and applied algorithms combination is very problem specific, therefore the task needs a case by case solution. The following set of quantitative requirements is considered as a generic baseline to verify the diagnostic performance of DFs:

- The system shall ensure a Diagnostic Capability Rate (DCR) of more than X%.
- The DF shall achieve a probability of detection of more than X%.
- The number of COM false alarms shall be less than X% of all COM failure detections.
- All DF shall ensure an error for damage quantification of less than X%.
- All DF shall ensure an uncertainty for damage quantification of less than X%.
- All DF shall ensure a probability of failure detection of more than X%.

The following definitions are used for these requirements:

- The DCR is defined as (FR_D = Failure Rates of components with diagnostic capabilities; FR_{SYS} = System Failure Rate):

$$DCR = \frac{\sum FR_D}{FR_{SYS}} \cdot 100 \qquad (1)$$

- Probability of detection shall be defined as the probability to detect the minimum detectable damage size.
- Uncertainty of damage quantification shall be defined as the X% probability for correct damage assessment.
- Probability of failure detection shall be defined as the probability to detect an exceedance of the maximum allowable damage size.

The capability to quantify incipient failures is seen as a prerequisite for prognostics, as the output from the DF will be used to predict the future state of the degradation.

2.2. Prognostics

The task of prognostics is to determine the point in time, from where on the specified requirements of a function cannot be satisfied anymore. The criterion of failure can be defined through an unacceptable deviation from any operating condition or the loss of functionality.

2.2.1. Classification of Prognostics

The different concepts for the implementation of prognostics can be divided into data-driven, model-based and hybrid approaches (Schwabacher, 2005, Medjaher et. al, 2013 and Goebel, Saha & Saxena, 2008):

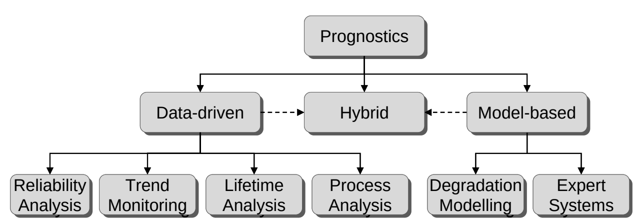

Figure 5. Classification of prognostic approaches

The Reliability Analysis is based on a statistical evaluation of collected failure modes and correlation with recorded operating conditions to derive an estimate of the useful life for a given usage profile. No information about the real status will be used. Conservative assumptions can minimize the risk of failure but the useful life consumption is overestimated and a mismatch between the real and theoretical usage profile rises the risk for a failure during operation (Jaloretto et. al, 2009). The Weibull analysis is one of the most popular methods for Reliability Analysis (Groer, 2000).

Trend Monitoring uses time series regression of selected features to extrapolate an observed trend to a predefined threshold. With a meaningful selection of features, it is possible to gain sufficient knowledge about the real status of the system and about the future trend of the health status. As Trend Monitoring is usually adapted to the incoming observations, the potential for inclusion of prior knowledge is limited (Maio & Zio, 2010). Trend monitoring is applied if the degradation process is not sufficiently known or the used parameters are built up by numerous processes and no comprehensive data-base for the development of damage propagation models is available. Various methods from the field of auto-regression are common practice for Trend Monitoring tasks (Pandian & Ali, 2010).

The Lifetime Analysis establishes a direct link between the current condition and the Remaining Useful Life (RUL) of the monitored item, without considering the real path of the degradation process (Gebraeel & Lawley, 2008).

Concepts from the data-driven Process Analysis domain are utilizing collected information about the degradation path and relevant operating conditions to identify a suitable damage propagation model. The identified model is then used to predict the degradation trend as a function of operating conditions and the current health status, until a predefined threshold is exceeded. Commonly used methods are Neural Networks (Rao et. al, 2012), Support Vector Machines (Khawaja & Vachtsevanos, 2009) or Fuzzy-Inference Systems (Javed et. al, 2011). The Gaussian Process is a quite new and powerful method for data-model identification through non-parametric regression (Liu et. al, 2013). The strength of data-driven process analysis can be seen in the wide field of applications and in the fact that no or only very limited prior knowledge about the underlying process is needed to derive a suitable model. Restrictions are mainly resulting from the limited applicability for extrapolation beyond the training data sets and the black-box character of the identified models. Additionally it cannot be guaranteed that the identified solution represents a global optimum of the problem, causing single fractions of the training data to have a higher weighting. Especially in the case of prognostics, this can cause divergence of the results (Wang & Wang, 2012).

Model-based techniques utilize detailed knowledge about the relationship between measurements, design parameters and the degradation trends to derive functional or physical models. The identification of model parameters and states shall enable an exact assessment of the monitored indicator and related uncertainties (model errors, measurements errors, bandwidth of operating conditions). For optimal support of the respective tasks, different models are used for identification (process model) and prediction (damage model) (Daigle et. al, 2012). The monitored state and all related uncertainties are estimated with the process model. The damage model is used to determine the degradation path until a predefined criterion is met. The most popular approaches are using recursive Bayesian estimators like the Kalman Filter for linear models (Celaya et. al, 2011), Extended Kalman Filter (Bechhoefer, 2008) and Unscented Kalman Filter for nonlinear models (Zhang & Pisu, 2012) and particle filter for non-Gaussian distributed variables and states (Zhu et. al, 2013).

Hybrid estimation schemes with multiple-model approaches optimize the local applicability of single models, improving quality of the overall prognostic performance and robustness (Li & Jilkov, 2003 and Chen, 2011).

Expert systems are based on a detailed technical understanding of the relationship and interactions between a Condition Indicator (CI) and the RUL. Fixed model structures or predefined decision trees are used to generate the estimate, without the capability to adapt the model structure to a new observation. With sufficient knowledge and experience, these approaches can enable an optimized prognosis but have a very limited robustness against model and measurement uncertainties (Brotherton, 2000).

Hybrid approaches combine the strengths from data- and model-based concepts to provide an optimized solution for the prognostic task. Common implementations are compensating measurement uncertainties or performing parameter estimation for data-driven concepts with adaptive filtering (Liu et. al, 2013) or provide data-modules to extend model structures with elements that cannot be modelled (Anger, Schrader, & Klingauf, 2012).

A qualitative overview about the fields of application for data-driven, model-based and hybrid concepts in general is depicted in Figure 6.

All mentioned prognostic approaches can be classified into two main categories:

- Lifetime calculation
- Failure prognosis

Only approaches that are enabling the prediction of the path for a CI under consideration of future operating conditions are accounted for the category of failure prognosis. This includes trend monitoring, selected data-driven process analysis concepts as well as model-based approaches, which are using damage propagation models or suitable expert systems.

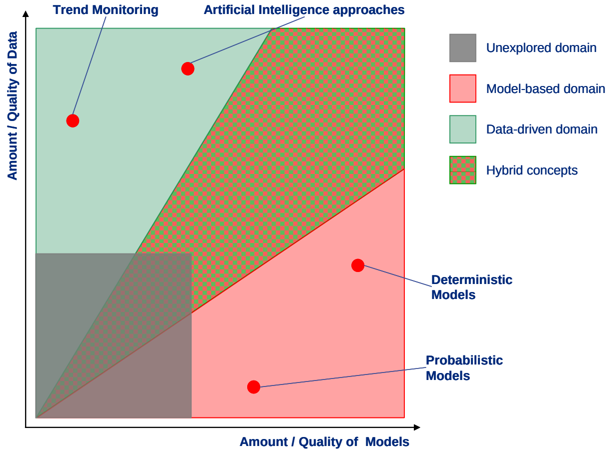

Figure 6. Areas of application for prognostic concepts

Exact determination of the CI and related uncertainties for damage quantification through appropriate DFs are a prerequisite for failure prognosis. The period for which the prognosis can satisfy certain accuracy and precision requirements is called prognostic horizon and indicates the potential for predictive measures like spare parts ordering or maintenance scheduling. For a definition of prognostic horizon the reader should refer to section 7 or to Saxena, Celaya, Balaban, Goebel, Saha B., Saha S. and Schwabacher 2008.

Every failure prognosis accumulates and integrates all uncertainties for damage quantification, prediction of damage trends and impact of future operating conditions: Prognostics deals therefore with uncertainty. In the last step of the DF, before the prognosis is started, uncertainties come from the imperfect data acquisition and representation of the underlying process of damage quantification as well as uncertain knowledge of future inputs. Since these sources of uncertainty cannot be avoided, the full prognostic task deals with variables like remaining useful life and end of life that are random in nature. For these reasons, every prognostic algorithm must account for these inherent uncertainties. Moreover every conceived algorithm contributes to increase the uncertainty of the overall framework: the conceived algorithm has in fact just a partial knowledge of the state of the system at the time in which a prediction is initialized, of the future input statistics, of the description of the underlying process and above all it does not know exactly which model the system will follow during the time interval of prediction.

All the above-mentioned considerations make then the prognostic process a highly stochastic task. The final aim of the full prognostic process is to support the risk management for predictive planning, by means of the reliable determination of the expected RUL and related confidence limits: therefore making decisions based on uncertain information needs the characterization of the uncertainty itself. Hence, a failure prognosis shall provide not simply the trend of a CI but the whole time-dependent probability density function of the predicted feature, with an over time increasing variance (Lybeck et. al, 2007).

The way in which uncertainty is handled is therefore of paramount importance: however not so many papers in the literature are dealing with uncertainty propagation (Sankararaman et. al, 2011, Saha, Quach & Goebel, 2012, Luo e. al, 2008, Edwards, Orchard, Tang, Goebel, & Vachtsevanos, 2010, Daigle, Saxena, & Goebel, 2012 and Candela, Girard, Larsen & Rasmussen, 2003) as far as the authors knowledge is concerned. In what follows a discussion regarding this topic will be provided. In particular, the problem of propagating the first two statistical moments (mean and variance) of a CI will be addressed together with the final derivation of the time-dependent probability of failure information (giving then the expected RUL, End of Life and the corresponding confidence limits).

First task of a generic prognostic process is to forecast the statistics of the CI: that is in other words to derive for future time instants its mean and variance or, if possible, the full Probability Density Function (PDF), that provides also the moments of higher order of the distribution.

Assuming that a model equation is available for the process describing the CI, the propagation of its statistics could be accomplished by considering the general equation (Eq. 3) proposed in the ISO Guide to the Expression of Uncertainty in Measurement (ISO/IEC Guide 98-3, 2008): an example of a generic model equation is here considered. The model equation is a function of Z number of inputs z_ζ, namely: x_χ ($\chi=1, 2, \ldots, X$); the time index k_t and the value that the function itself assumed a time-step before (a generic lag-dependency of course can here be considered).

$$\begin{aligned} CI &= CI(z_1, z_2, \ldots, z_Z) = \ldots \\ & CI(k_t, x_1, x_2, \ldots x_X, CI(k_{t-1})) \end{aligned} \tag{2}$$

Considering the simplified circumstances in which inputs have no cross-correlation, the uncertainty u of the CI can be expressed by means of the following equation:

$$u(CI) = \sqrt{\sum_{\zeta=1}^{\zeta=Z} \left[\left(\frac{\partial CI}{\partial z_\zeta} \right) \cdot u_\zeta^2(z_\zeta) \right]} \tag{3}$$

In which the uncertainty corresponding to each input propagates through the partial derivative with respect to the input itself; the derivative can be therefore thought as a sensitivity factor. Following the test-case suggested by (Eq.4), in Figure 7 the result from the uncertainty propagation of a model equation with $X=2$ is shown (reasonable u_{x1} and u_{x2} values have been assumed regarding the inputs uncertainty, 30% and 15% of the respective definition's domains of x_1 and x_2), whilst time index is considered a certain information).

$$
\begin{aligned}
&CI = CI_1(x_1) + CI_2(x_2) + \ldots \\
&CI_3(k_t, x_1, x_2) + CI_4(CI(k_{t-1})) \\
&CI_1 = c \cdot e^{x_1} + \sum_{r=0}^{r=R} a_r \cdot x_1^r;\ CI_2 = \sum_{s=0}^{s=S} b_s \cdot x_2^s; \\
&CI_3 = 2 \cdot k_t + x_1 \cdot x_2 \cdot k_t^2;\ CI_4 = d \cdot \sqrt{CI(k_{t-1})}
\end{aligned}
\tag{4}
$$

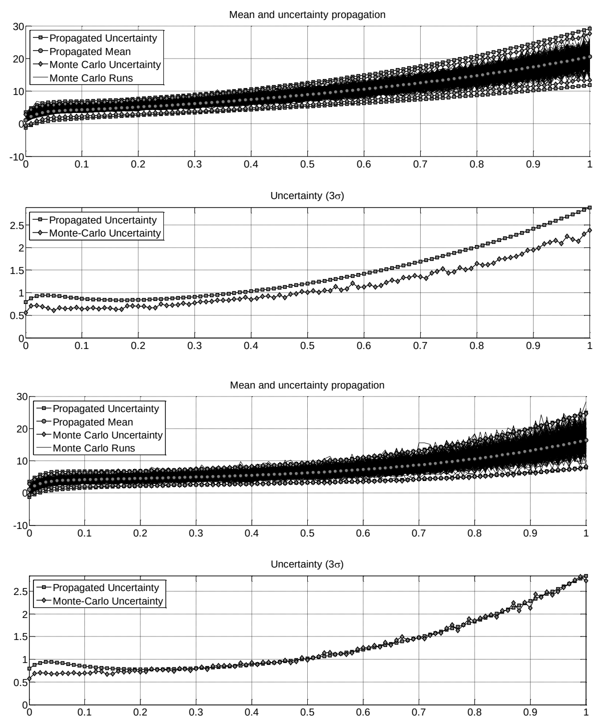

Figure 7. Mean and variance propagation

More in detail, the upper couple of pictures shows the prediction for a model equation with $R=S=5$ (highly non-linear; see Eq. 4) whilst the lower couple of pictures has R=S=2. The upper pictures stress the possible issues with this approach (in what follows as uncertainty has been always considered three times the value of the corresponding standard deviation): the reliability and accuracy of the uncertainty propagation decreases as the non-linearity of the system increases. The more the system has a non-linear behavior, the more the uncertainty propagation through the use of the partial derivatives fails, since the first derivative alone is not able to capture the full dynamic. As a matter of fact, the predicted uncertainty takes values apart from the *real ones* that are calculated by means of a Monte-Carlo simulation. Moreover, the approach here used, and based on the ISO Guide above mentioned, tackles only situations, in which we have at our disposal a closed form equation. If a recursion takes place, for example if a state-space-based system is used in which the previous state estimation is used as input to the current estimation step, then the approach, as here has been presented, is not applicable.

However, the above requirements are not always fulfilled, and therefore for many models the predictive density can only be approximated using Monte-Carlo sampling, local expansions or variational approaches. In these cases a Bayesian approach is generally followed (Daigle, Saxena, & Goebel, 2012 and Candela, Girard, Larsen & Rasmussen, 2003); the Bayesian kernel methods have proven to be very efficient nonlinear models (Rasmussen, 1996 and Quinonero-Candela & Hansen, 2002) with flexible approximation capabilities and high generalization performance. As known, recursive sequential Bayesian filters are probabilistic approaches adopted to estimate an unknown PDF recursively over time; they make use of a mathematical process model and of incoming measurements. The estimation consists of two steps, namely prediction and correction: within the prediction step, the system state is projected in time towards a future state using the process model; then, by means of the incoming measurements, the statistics of the system are updated. The described framework could then be adapted within a prognostic task, applying a multi-step ahead prediction, assuming no more measurements will be available. The mathematics beneath the Bayesian filter remains the same, but the correction step. In fact, having no measurements, the error is assumed to be zero. This way the mean and variance of a CI are reasonably forecasted.

Remaining within the Bayesian modelling, in (Daigle, Saxena, & Goebel, 2012) a different approach is proposed. Here the authors have developed a sample-based algorithm for predicting the remaining useful life distribution, accounting for the different sources of uncertainties. By adopting the unscented transformation (Julier & Uhlmann, 2004), the method allows one to sample from future input trajectories, maintaining at the end of the prediction the statistics as well. Moreover, having the unscented transformation deterministically accomplished, RUL predictions are deterministically bounded as well (and this is - in safety-critical systems - of great importance, if we think to the verification, validation, and certification protocols in the aerospace domain). In (Candela, Girard, Larsen & Rasmussen, 2003), Gaussian Process and Relevant Vector Machine approaches are used to propagate uncertainty. The paper aims to increase the prediction reliability by taking into consideration also the uncertainty associated to predicted values that are recursively used within the multiple-step ahead forecasting. A novel analytical expression is in fact derived for the predicted mean and variance.

Regardless of the approach followed, the first task of a prognostic process is to forecast the statistics of the CI, so that one has at his disposal the PDF of CI for future time ($PDF_{CI,t}$). In order to determine the so called Probability of

Failure (PoF) of the unit under investigation, the statistics (in terms - for example - of the Cumulative Distribution Function - CDF) of the value assumed by the CI corresponding to failed conditions CDF_{CI} has to be known; this can be derived experimentally or assumed with common engineering sense.

This way PoF_t, indicating the probability that the monitored component fails at time *t*, can be derived:

$$PoF_t = \int_{CI=0}^{CI=\infty} PDF_{CI,t} \cdot CDF_{CI} \cdot \partial CI \qquad (5)$$

From this distribution could be derived then the expected RUL (that is corresponding to the time at which the PoF i.e. is equal to 0.5 or 50%) and/or other needed confidence limits. In the following figure, the resulting PoF is shown, together with two different forecasted PDFs of the CI and the probability density function from which the CDF_{CI} is derived.

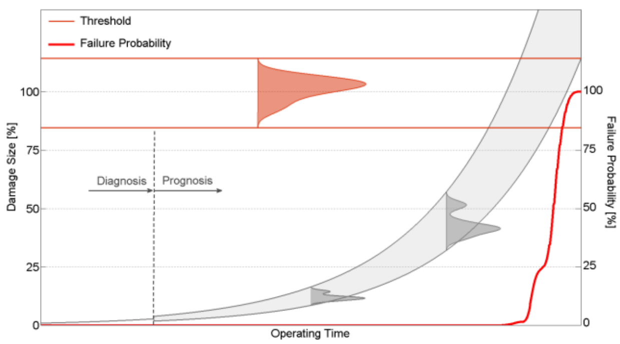

Figure 8. Failure Prognosis with distributed threshold

To maximize the use of prognostics, the expected RUL has to be estimated with high accuracy and low uncertainty. The quality of prognosis increases with the prognostic horizon and the level of convergence of the expectation value and confidence limits against the real degradation path. The most important aspect for capitalization of prognostics is the accurate RUL estimation when the spare parts are ordered and condition-based maintenance is scheduled.

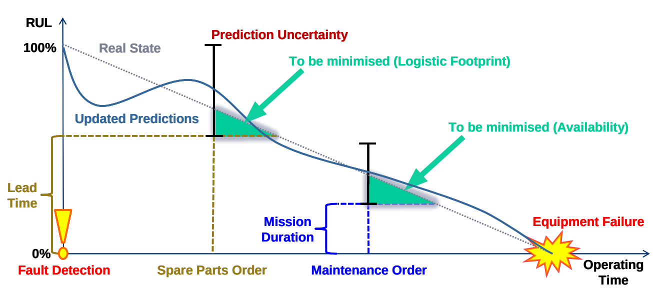

Figure 9. Impact of prognostic performance on logistics and maintenance scheduling

The potential for optimization of the logistic and maintenance process is inversely proportional to the deviation between the real and predicted values and the related uncertainties. These interrelations are depicted in Figure 9.

2.2.2. Development of Prognostics

The development of prognostics can be seen as a special case of software development, as the verification of the prognostic capabilities usually is very cost and time consuming and requires many test cases to prove the accuracy and precision of prediction. Since legacy systems usually do not provide the type and quality of information that is needed to support the development of failure prognosis, then the need to perform destructive testing for a new system design will highly adversely affect the development cost and time schedule for the certification of the operating system. The limiting factors for the realization of a predictive decision support are shown in Figure 10. The overall limit for the development of prognostic concepts is represented by the technology's maturation regarding data collection and available prognostic algorithms; for this reason the particular design, expressed through the required prognostic performance, will be defined by the application for economical, mission or safety critical functions. Moreover, due to the fact that autonomous mission support functions would require on-board applications, the integration into the off-board environment will enable the usage of more computing resources, extending so the list of applicable concepts and access to stored data.

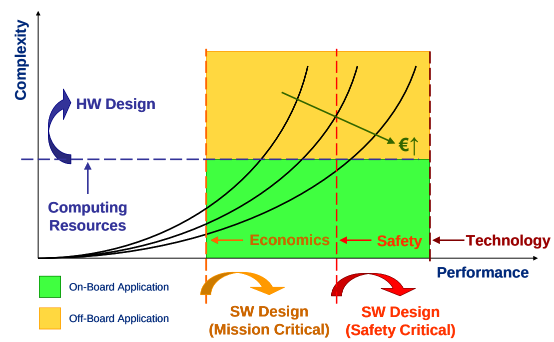

Figure 10. Considerations for development of Prognostics

As discussed in section 2.2.1, a variety of different approaches exist to implement Prognostic Functions (PFs). The quality/quantity of available degradation data and prior knowledge about the physics of degradation are determining whether data-driven or model-based approaches should be favored. After the initial decision about the type of solution that will be followed, a concept is needed to investigate advantages and disadvantages of different implementations and assess their prognostic performance during the design phase. Airbus Defence & Space has developed a framework to support these tasks and to enable prioritization of the most suitable prognostic approach without consideration of cost elements (see Figure 11).

The shown process aims for a stepwise evaluation of selected performance metrics, successively enhancing the database for prognosis by increasing the number of used training datasets. The verification of prognostic capabilities is done for each test dataset $k = 1{:}Q$, whereas each single set is composed of $i = 1{:}N$ time increments for starting the prognosis.

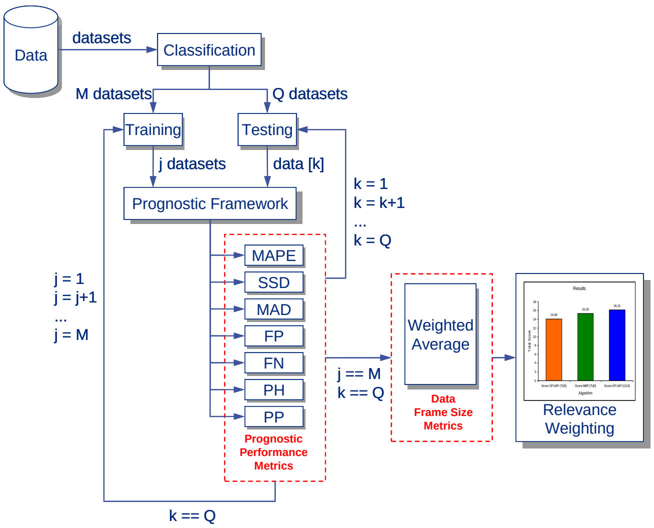

Figure 11. Framework for assessment of prognostic performance

In what follows, a set of general definitions will be provided (see Figure 12) regarding the conceived process: up to time t_0, diagnostic information is collected and used to derive the current health status and uncertainties for damage quantification, the item fails at EoL with a real remaining useful life of RUL. The prognosis starts at t_0 and estimates the predicted remaining useful life RUL*, with EoP (End of Prediction) as the point in time when the forecasted indicator distribution (the PDF of CI) is such that the cumulative of the PoF exceeds 50%. The upper and lower confidence limits of RUL* predictions are denoted by RUL_{UL}* and RUL_{LL}* respectively (UL (or ul): Upper Limit; LL (or ll): Lower Limit).

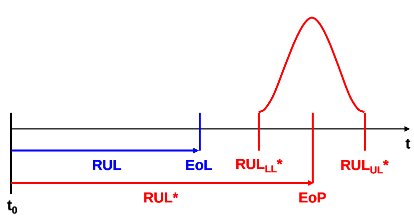

Figure 12. Definitions for prognostics

According to the general approach for system identification tasks, a prerequisite for performance evaluation is to classify the available data into "known" training data and "unknown" test data. All training data can be used for the development of prognostic concepts, while the test data should be used for verification of the prognostic performance. The classification into training and test data should follow a structured approach, to ensure that the information content is comparable and the results are representative for the achievable performance of the tested prognostic concept. Dedicated test cases for evaluation of limitations and robustness can be added at a later stage.

To simplify the comparison of results for different test runs k, the time dependency of the datasets can be normalized, by replacing the usage time T (in calendar time, cycles or operating hours) by a unitless value λ for all time increments:

$$\lambda_{1:N,k} = \frac{T_{1:N,k}}{RUL_k} = [\lambda_0, \ldots, 1] \tag{6}$$

with:
$$T_{1,k} = t_{0k}$$

$$T_{N,k} = EoL_k$$

The prognostic error ε needs to be calculated for each individual test run and λ-step of $RUL^*_{i,k}$:

$$\varepsilon_{i,k} = RUL_k - RUL^*_{i,k} \tag{7}$$

The same is required for the upper and lower confidence limits of RUL predictions:

$$\varepsilon ul_{i,k} = RUL_k - RUL_{UL}{}^*_{i,k} \tag{8}$$

$$\varepsilon ll_{i,k} = RUL_k - RUL_{LL}{}^*_{i,k} \tag{9}$$

For a consistent prognosis, the relative difference between EoL and EoP should reduce towards zero with increasing damage size, as the equipment approaches EoL. To account for that higher relevance of later predictions (increasing λ), an exponential scaling factor ρ is introduced:

$$\rho_{1:N,k} = \exp\left(\left(\lambda_{1:N,k} - \arg\max\left\{\lambda_{1:N,k}\right\}\right)\cdot w\right) \tag{10}$$

Where w denotes a factor for relevance weighting of the different predictions (see Figure 13).

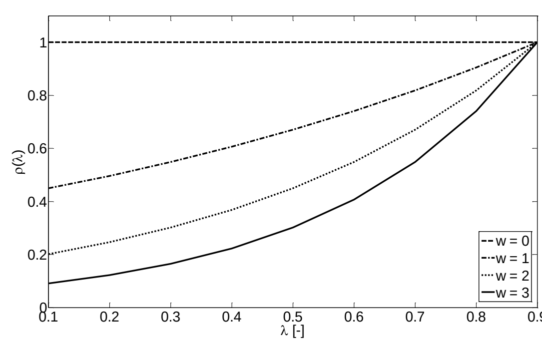

Figure 13. λ relevance weighting for performance criteria

Based on the contents of (Saxena et. al, 2008), the following criteria have been derived to support the identification of the most suitable prognostic approach:

1. Mean Absolute Percentage Error (MAPE):

$$MAPE_k = \frac{\sum_{i=1}^{N} \rho_i \cdot \left| \frac{\varepsilon_{i,k}}{RUL_{i,k}} \right| \cdot 100}{\sum_{i=1}^{N} \rho_i} \tag{11}$$

2. Sample Standard Deviation (SSD):

$$SSD_k = \sqrt{\frac{\sum_{i=1}^{N} \rho_i \cdot \left(\varepsilon_{i,k} - \bar{\varepsilon}_k\right)^2}{\sum_{i=1}^{N} \rho_i - \bar{\rho}}} \tag{12}$$

with:

$$\bar{\varepsilon}_k = \frac{1}{N} \cdot \sum_{i=1}^{N} \varepsilon_{i,k}$$

$$\bar{\rho} = \frac{1}{N} \cdot \sum_{i=1}^{N} \rho_i$$

The SSD criterion is applicable for Gaussian distributions of $\varepsilon_{i,k}$.

3. Mean Absolute Deviation from Median (MAD):

$$MAD_k = \frac{\sum_{i=1}^{N} \rho_i \cdot \left(\varepsilon_{i,k} - \tilde{\varepsilon}_k\right)}{\sum_{i=1}^{N} \rho_i - \bar{\rho}} \tag{13}$$

with: $\tilde{\varepsilon}_k = median(\varepsilon_{1:N,k})$

The MAD criterion is applicable for non-Gaussian distributions of $\varepsilon_{i,k}$.

4. False Positives (FP):

$$FP_k = \sum_{i=1}^{N} \delta_{FPi,k} \begin{cases} \delta_{FPi,k} = 1, \forall \varepsilon ul_{i,k} > 0 \\ \delta_{FPi,k} = 0, \forall \varepsilon ul_{i,k} \le 0 \end{cases} \tag{14}$$

The FP criterion identifies the predictions that would cause an unacceptable early replacement, affecting operational availability adversely.

5. False Negatives (FN):

$$FN_k = \sum_{i=1}^{N} \delta_{FNi,k} \begin{cases} \delta_{FNi,k} = 1, \forall \varepsilon ll_{i,k} < 0 \\ \delta_{FNi,k} = 0, \forall \varepsilon ll_{i,k} \ge 0 \end{cases} \tag{15}$$

The FN criterion identifies the predictions that would cause an unacceptable late replacement, affecting safety adversely.

6. α-λ Performance:

The α-λ metric is used to identify the point in time from where on the predicted RUL remains within the confidence limits given by f_1 and f_2 (Eq. (16) & Eq. (17), see shaded region in Figure 14):

$$f_{1,1:N,k} = \left[(1+\alpha) \cdot \frac{\left(RUL_{1:N,k} + t_{0k}\right)}{EoL_k} \right] \cdot 100 \tag{16}$$

$$f_{2,1:N,k} = \left[(1-\alpha) \cdot \frac{\left(RUL_{1:N,k} + t_{0k}\right)}{EoL_k} \right] \cdot 100 \tag{17}$$

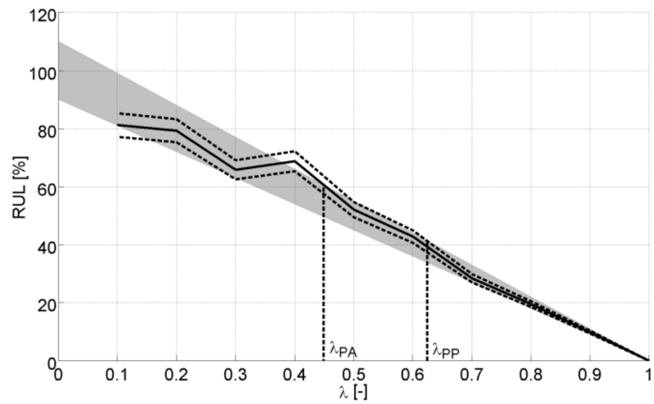

Figure 14. α-λ plot with α = 10%

Two performance values can be derived from the α-λ analysis (see Figure 14):

<u>Prognostic Accuracy (PA):</u>

Point from where on the average of RUL predictions remains stable within the given α-limits ($\lambda_{PA,k}$).

<u>Prognostic Precision (PP):</u>

Point from where on both confidence limits of RUL predictions remain stable within the given α-limits ($\lambda_{PP,k}$).

7. Prognostic Horizon (PH):

The PH-metric indicates the point in time ($\lambda_{PH,k}$) from where on the predictions stay stable within the confidence limits given by g_1 and g_2 (Eq. (18) & E. (19), see shaded region in Figure 15):

$$g_{1,1:N,k} = \left[\frac{\left(RUL_{1:N,k} + t_{0k}\right)}{EoL_k} + \alpha \right] \cdot 100 \tag{18}$$

$$g_{2,1:N,k} = \left[\frac{\left(RUL_{1:N,k} + t_{0k}\right)}{EoL_k} - \alpha \right] \cdot 100 \tag{19}$$

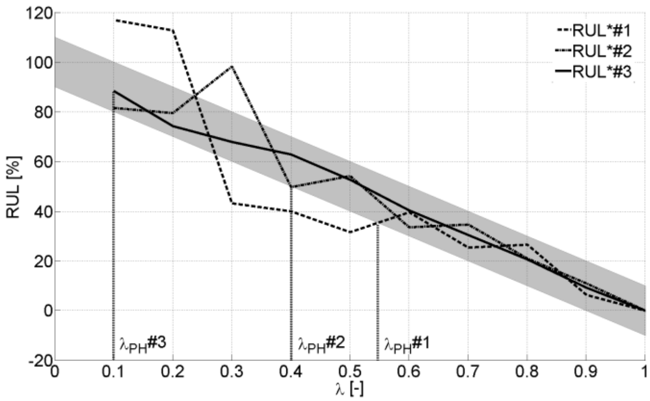

Figure 15. Prognostic Horizon plot with α = *10%*

The resulting performance values $p_{l,1:M}$ are simply the arithmetic means of the applied "Prognostic Performance Metrics".

Additional criteria are needed if the evolution of the prognostic performance with an increasing number of training datasets $j = 1:M$ shall be considered. These criteria are defined as "Data Frame Size Metrics" to account for the dimensions of the training datasets. Therefore the weighted average υ_l of each criterion $p_{l,1:M}$ and each training dataset $m_{1:M}$ is used to assess the capability for continuous improvement during the life cycle:

$$\upsilon_l = \frac{\sum_{j=1}^{M} q_j \cdot p_{l,j}}{\sum_{j=1}^{M} q_j} \tag{20}$$

with $$q_j = \exp\left(\left(\dim(m_j) - \arg\max\{\dim(m_j)\}\right) \cdot w\right)$$

Where q_j denotes a weighting factor, addressing more relevance to the datasets including more information with $dim(m_j)$ as the dimension of training data used in dataset m_j.

If a unique resulting performance value is needed to simplify the comparison of different approaches, a weighted average of all criteria $\upsilon_{1:L}$ can be used. The individual weighting should reflect the relevance of the respective criterion. Independent of the type of application, the FN and PH criteria shall have a high weighting, as they are representing the risk for failure during operation and the prognostic lead time for predictive planning.

Similar to other conventional design tasks from the field of HW or SW development, prognostics do also need the definition of design requirements, which can be used to perform validation & verification during the design stage of a new system. To support this task, the following qualitative requirements have been identified as relevant for the development of PF:

- The unit for RUL estimations (time-based, cycle-based or calendar-based) shall be predefined for each PF.
- The PF shall enable prognosis from entering into service without availability of comprehensive data sets.
- The PF shall provide capabilities for continuous improvement over the life cycle of the operating system.
- The PF shall enable evaluation of different future operating profiles.
- Determination of a suitable condition indicator for damage quantification and related uncertainties shall be the task of a diagnostic system and be provided to the PF.
- The process for achieving prognostic capabilities as well as the prognosis itself must not be real-time capable.
- The PF shall provide uncertainty estimates for RUL predictions to support risk analysis for logistics and maintenance scheduling.
- Evaluation of selected criteria shall enable assessment of the prognostic performance and design requirements.

These conceptual requirements can be seen as general design guidelines for the development of PF. One major issue for the development of prognostics is the need to verify the capability to predict future states with a predefined accuracy and robustness. Therefore quantitative requirements are needed in addition to the set of qualitative ones given above, that enable the evaluation of uncertain test results. Based on previous studies regarding suitable approaches for performance assessment of prognostic functions (Saxena et. al, 2008), Airbus Defence & Space has derived a set of quantitative requirements that can be used for verification of the performance of any PF:

- The system shall ensure a Prognosis Capability Rate (PCR) of more than X%.
- The absolute Percentage Error (PE) of RUL predictions shall always be less than X% of the actual RUL.
- The Uncertainty of RUL Predictions (PU) shall always be less than X% of the predicted RUL.
- The prognostic function shall achieve a False Positives Rate (FPR) of less than X%.
- The prognostic function shall achieve a False Negatives Rate (FNR) of less than X%.

The following definitions are used for these requirements:

- The Prognosis Capability Rate PCR is defined as (FR_P = Failure Rates of components with prognostic capabilities; FR_{SYS} = System Failure Rate):

$$PCR = \frac{\sum FR_P}{FR_{SYS}} \cdot 100 \tag{21}$$

- The Percentage Error of RUL predictions PE is defined as:

$$PE = \frac{RUL_{50\%PoF} - RUL}{RUL} \cdot 100 \tag{22}$$

- The Uncertainty of RUL Predictions PU is defined as:

$$PU = \frac{RUL_{95\%PoF} - RUL_{5\%PoF}}{RUL_{50\%PoF}} \cdot 100 \tag{23}$$

- False Positives Rate is defined as:

$$FPR = \frac{RUL_{50\%PoF} - RUL}{RUL} \cdot 100 < -X\% \tag{24}$$

- False Negatives Rate is defined as:

$$FNR = \frac{RUL_{50\%PoF} - RUL}{RUL} \cdot 100 > +X\% \tag{25}$$

These requirements are covering all relevant aspects that are needed to verify the performance and robustness of a PF during the development stage and for performance monitoring during service.

3. CONCLUSION

The implementation of enhanced health monitoring and failure prognosis functions is one prerequisite to enable condition-based operations. The motivation for the development of such capabilities is driven from the need to establish competitive solutions for aerospace applications, enhancing availability and mission reliability, while reducing operation & support costs. The development of an integrated health management system requires dedicated requirements and processes for identification of the optimal problem specific solutions for diagnostics & prognostics and to enable validation & verification during the system design stage. The concept for requirements definition and prognostic performance evaluation presented in this paper has been successfully applied during preceding development programs. Future research activities will focus on the extension of the requirements framework with concepts for cost-benefit analyses to further maturate the development framework for diagnostic & prognostic functions.

NOMENCLATURE

Symbols

α	Accuracy value for performance evaluation
ε	Prognostic error
E	Waste of useful life
L	Number of Prognostic Performance Criteria
m_j	Training dataset for prognostics
M	Number of datasets for training of prognostics
p	Prognostic performance criterion
Q	Number of datasets for testing of prognostics
T	Operating Time
υ	Data frame size metric

Abbreviations

BIT	Build-In-Test
CDF	Cumulative Distribution Function
CI	Condition Indicator
COM	COndition Monitoring Function
DCR	Diagnostics Capability Rate
DF	Diagnostic Function
EoL	End of Life
EoP	End of Preditiction
FN	False Negatives
FP	False Positives
FPR	False Positives Rate
FNR	False Negatives Rate
LL (ll)	Lower Limit
MAD	Mean Absolute Deviation from Median
MAPE	Mean Absolute Percentage Error
PA	Prognostic Accuracy
PBC	Performance Based Contracting
PCR	Prognostics Capability Rate
PDF	Probability Density Function
PE	Absolute Percentage Error of RUL predictions
PF	Prognostic Function
PH	Prognostic Horizon
PHM	Prognostics and Health Management
PP	Prognostic Precision
PU	Uncertainty of RUL predictions
RUL	Remaining Useful Life
*RUL**	Remaining Useful Life predictions
SSD	Sample Standard Deviation
UL (ul)	Upper Limit

REFERENCES

Anger, C., Schrader, R. & Klingauf, U. (2012). Unscented Kalman Filter with Gaussian Process Degradation Model for Bearing Fault Prognosis. *Proceedings of the First European Conference of the Prognostics and Health Management Society 2012*. July 2-5, Dresden, Germany

Bechhoefer, E. (2008). A Method for Generalized Prognostics of a Component Using Paris Law. *Proceedings of American Helicopter Society 64th Annual Forum 2008*. April 29 - May 1, Montreal, Canada

Brotherton, T. (2000). Prognosis of Faults in Gas Turbine Engines. *Proceedings of IEEE Aerospace Conference*. March 18-25, Big Sky, Montana, USA. doi: 10.1109/AERO.2000.877892

Candela, J.Q., Girard, A., Larsen, J. & Rasmussen, C.E. (2003). Propagation of uncertainty in Bayesian kernel models - application to multiple-step ahead forecasting.

Proceedings of the International Conference on Acoustics, Speech, and Signal Processing. April 1-6, Hong Kong, China

Celaya, J.R., Kulkarni, C., Biswas, G., Saha, S. & Goebel, K. (2011). A Model-based Prognostics Methodology for Electrolytic Capacitors Based on Electrical Overstress Accelerated Aging. *Proceedings of the Annual Conference of the Prognostics and Health Management Society*. September 25-29, Montreal, Quebec, Canada

Chen, H. (2011). A Multiple Model Prediction Algorithm for CNC Machine Wear PHM. *International Journal of Prognostics and Health Management 2011*, issue 2. ISSN2153-2648

Chung-Chien, C. & Cheng-Ching, Y. (1990). On-Line Fault Diagnosis Using the Signed Directed Graph. *Industrial & Engineering Chemistry Research*, vol. 29, pp. 1290-1299. doi: 10.1021/ie00103a031

Crepin, P.Y. & Kreß, R. (2000). Model Based Fault Detection for an Aircraft Actuator. *Proceedings of the International Council of the Aeronautical Sciences.* August 28 - September 1, Harrogate, UK

Daigle, M., Saha, B. & Goebel, K. (2012). A Comparison of Filter-based Approaches for Model-based Prognostics. *Proceedings of IEEE Aerospace Conference*. March 3-10, Big Sky, Montana, USA. doi: 10.1109/AERO.2012.6187363

Daigle, M., Saxena, A. & Goebel, K. (2012). An Efficient Deterministic Approach to Model-based Prediction Uncertainty Estimation. *Proceedings of the First European Conference of the Prognostics and Health Management Society*. July 2-5, Dresden, Germany

Edwards, D., Orchard, M. E., Tang, L., Goebel, K., & Vachtsevanos, G. (2010). Impact in input uncertainty on failure prognostic algorithms: Extending the remaining useful life of nonlinear systems. *Proceedings of the Annual Conference of the Prognostics and Health Management Society*. October 10-16, Portland, Oregon, USA

Gebraeel, N.Z. & Lawley, M.A. (2008). A Neural Network Degradation Model for Computing and Updating Residual Life Distributions. *IEEE Transactions on Automation Science and Engineering*, vol. 5, issue 1, pp. 154-163

Goebel, K., Saha, B. & Saxena, A. (2008). A Comparison of three Data-Driven Techniques for Prognostics. *Proceedings of the 62nd Meeting of the Society for Machinery Failure Prevention Technology*. April 6-8, Virginia Beach, Virginia, USA

Groer, P.G. (2000). Analyses of Time-To-Failure with a Weibull Model. *Proceedings of the Maintenance and Reliability Conference*. May 8-10, Knoxville, Tennessee, USA

Hunt, S.R. & Hebden, I.G. (1998). Eurofighter 2000 An Integrated Approach to Structural Health and Usage Monitoring. *RTO AVT Specialists Meeting on "Exploitation of Structural Leads/Health Data for Reduced Life Cycle Costs"*. May 11-12,. Brussels, Belgium

Isermann, R. (1992). *Identifikation dynamischer Systeme I - Grundlegende Methoden*. Springer-Verlag

Isermann, R. (2006). *Fault Diagnosis Systems*. Springer-Verlag

ISO/IEC Guide 98-3:2008 *Uncertainty of measurement - Part 3: Guide to the expression of uncertainty in measurement (GUM:1995)*

Jaloretto, M.R., Bizarria, C. & Galvao, R. (2009). Trend Analysis for Prognostics and Health Monitoring. *Brazilian Symposium on Aerospace Eng. & Applications*. September 14-16, S.J. Campos, SP, Brazil

Javed, K., Gouriveau, R., Zemouri, R. & Zerhouni, N. (2011). Improving Data-Driven Prognostics by Assessing Predictability of Features. *Annual Conference of the Prognostics and Health Management Society*. September 25-29, Montreal, Quebec, Canada

Jazouli, T. & Sandborn, P. (2011). Using PHM to Meet Availability-Based Contracting Requirements. *Proceedings of IEEE Aerospace Conference*. March 5-12, Big Sky, Montana, USA

Julier, S. J. & Uhlmann, J. K. (2004). Unscented filtering and nonlinear estimation. *Proceedings of the IEEE*, vol. 92, issue 3, pp. 401–422. doi: 10.1109/JPROC.2003.823141

Kacprzynski, G.J., Liberson, A., Palladino, A., Roemer, M.J., Hess, A.J. & Begin, M. (2004). Metrics and development tools for prognostic algorithms. *Proceedings of IEEE Aerospace Conference 2004*. March 6-13, Big Sky, MT, USA. doi: 10.1109/AERO.2004.1368198

Khawaja, T. & Vachtsevanos, G. (2009). A novel Architecture for on-line Failure Prognosis using Probabilistic Least Squares Support Vector Regression Machines. *Proceedings of the Annual Conference of the Prognostics and Health Management Society*. September 27 – October 1, San Diego, California, USA

Kühl, T. & Pakszies, A. (2011). Condition Monitoring of Civil Jet Engines during Flight. *LTH Triebwerkstechnologie*, AT 58 100-01

Leao, B.P., Yoneyama, T., Rocha, G.C. & Fitzgibbon, K.T. (2008). Prognostics Performance Metrics and their Relation to Requirements, Design, Verification and Cost-Benefit. *International Conference on Prognostics and Health Management*. October 6-9, Denver, CO, USA. doi: 10.1109/PHM.2008.4711429

Lee, S.G., Ma, Y.-S., Thimm, G.L. & Verstraeten, J. (2008). Product lifecycle management in aviation maintenance, repair and overhaul. *Computers in Industry*, vol. 59, issues 2–3, pp. 296–303

Li, X.R. & Jilkov, V.P. (2003). A Survey of Maneuvering Target Tracking-Part V: Multiple-Model Methods. *IEEE Transactions on Aerospace and Electronic Systems*, vol. 41, issue 4, pp. 1255-1321. doi: 10.1109/TAES.2005.1561886

Liu, D., Guo, L., Pang, J. & Peng, Y. (2013). A Fusion Framework with Nonlinear Degradation Improvement for Remaining Useful Life Estimation of Lithium-ion Batteries. *Proceedings of the Annual Conference of the Prognostics and Health Management Society 2013*. October 14-17, New Orleans, Louisiana, USA

Liu, D., Pang, J., Zhou, J., Peng, Y., Pecht, M. (2013). Prognostics for State of Health Estimation of Lithium-Ion Batteries based on Combination Gaussian Process Functional Regression. *Microelectronics Reliability*, vol. 53, Issue 6, pp. 832-839

Luo, J., Pattipati, K. R., Qiao, L., & Chigusa, S. (2008). Model-based prognostic techniques applied to a suspension system. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, vol. 38, Issue 5, pp. 1156-1168. doi: 10.1109/TSMCA.2008.2001055

Lybeck, N., Marble, S., Morton, B. (2007). Validating Prognostic Algorithms: A Case Study Using Comprehensive Bearing Fault Data. *IEEE Aerospace Conference 2007*. March 3-10, Big Sky, Montana, USA

Zio, E., Maio, F.D., (2010). A Data-Driven Fuzzy Approach for Predicting the Remaining Useful Life in Dynamic Failure Scenarios of a Nuclear System. *Reliability Engineering & System Safety*, vol. 95, Issue 1, pp. 49-57

Medjaher, K., Zerhouni, N., Baklouti, J. (2013). Data-Driven Prognostics Based on Health Indicator Construction: Application to PRONOSTIA’s Data. *European Control Conference 2013*. July 17-19, Zurich, Switzerland

Mikat, H., Siddiolo, A.M., Buderath, M. (2012). Virtual Framework for Validation and Verification of System Design Requirements to enable Condition Based Maintenance. *European Conference of the Prognostics and Health Management Society 2012*. July 3-5, Dresden, Germany

Münchhof, M. (2006), *Model-based Fault Detection for a Hydraulic Servo Axis*. Doctoral dissertation. Technische Universität Darmstadt, Darmstadt, Germany

Pandian, A., Ali, A. (2010). A Review of Recent Trends in Machine Diagnosis and Prognosis Algorithms. *Reliability Engineering & System Safety*, vol. 95, Issue 1, pp. 49-57

Pipe, K. (2003). Measuring the Performance of a HUM System - Features that Count. *Proceedings of the 3rd DSTO International Conference on Health and Usage Monitoring*. February 17-18, Melbourne, Australia

Quinonero-Candela, J., Hansen, L.K. (2002). Time series prediction based on the relevance vector machine with adaptive kernels. *International Conference on Acoustics, Speech, and Signal Processing*, vol. 1, pp. 985-988, doi: 10.1109/ICASSP.2002.5743959

Rao, B.K.N., Srinivasa, Pai, P., Nagabhushana, T.N. (2012). Failure Diagnosis and Prognosis of Rolling - Element Bearings using Artificial Neural Networks: A Critical Overview. *Journal of Physics: Conference Series*, vol. 364, Issue 1

Rasmussen, C.E. (1996). *Evaluation of Gaussian Processes and Other Methods for Non-linear Regression*. Doctoral dissertation., University of Toronto, Toronto

Reimann, J., Kacprzynski, G., Cabral, D., Marim, R. (2009). Using Condition Based Maintenance to Improve the Profitability of Performance Based Logistic Contracts. *Annual Conference of the Prognostics and Health Management Society 2009*. September 27-October 1, San Diego, California, USA

Saha, B., Quach, C. C., & Goebel, K. (2012). Optimizing battery life for electric UAVs using a Bayesian framework. *Proceedings of the IEEE Aerospace Conference 2012*. March 3-10, Bis Sky, Montana, USA

Sankararaman, S., Ling, Y., Shantz, C., & Mahadevan, S. (2011). Uncertainty quantification in fatigue crack growth prognosis. *International Journal of Prognostics and Health Management 2011*, vol. 2, Issue 2

Saxena, A., Celaya, J., Balaban, E., Goebel, K., Saha, B., Saha, S. and Schwabacher, M. (2008). Metrics for Evaluating Performance of Prognostic Techniques. *International Conference on Prognostics and Health Management 2008*. October 6-9, Denver, Colorado, USA

Saxena, A., Roychoudhury, I., Celaya, J.R., Saha, S., Saha, B. (2010). Requirements Specifications for Prognostics: An Overview. *American Institute of Aeronautics and Astronautics*

Schaab, J. (2011). *Trusted Health Assessment of Dynamic Systems Based on Hybrid Joint Estimation*. Doctoral dissertation. Technische Universität Darmstadt, Darmstadt, Germany

Schaab, J., Harrington, M. and Klingauf, U. (2007). On-board Health Assessment of an Electro-mechanical Actuator Using Wavelet Features. *Proceedings of the 1st CEAS European Air and Space Conference 2007*. September 10-13, Berlin, Germany

Schwabacher, M.A., (2005). A Survey of Data-Driven Prognostics. *American Institute of Aeronautics and Astronautics*

Srivastra, A.N., Mah, R.W., Meyer, C. (2009). Integrated Vehicle Health Management. *NASA Aviation Safety Program*, Technical Plan 2009

Venkat, V., Raghunathan, R., Kewen, Y. and Suryari, N.K. (2003). A review of process fault detection and diagnosis Part I: Quantitative model-based methods. *Computers and Chemical Engineering 2003*, vol. 27, Issue 3, pp. 293-311

Venkat, V., Raghunathan, R., Kewen, Y. and Suryari, N.K. (2003). A review of process fault detection and diagnosis Part II: Qualitative models and search strategies. *Computers and Chemical Engineering 2003*, vol. 27, Issue 3, pp. 313-326

Venkat, V., Raghunathan, R., Kewen, Y. and Suryari, N.K. (2003). A review of process fault detection and diagnosis Part III: Process history based methods. *Computers and Chemical Engineering 2003*, vol. 27, Issue 3, pp. 327-346

Wang, Y., Wang, W. (2012). Failure Prognostic of Systems with Hidden Degradation Process. *Journal of Systems Engineering and Electronics*, vol. 23, Issue 2, pp. 314-324, doi: 10.1109/JSEE.2012.00039

Wilmering, T.J., Ramesh, A.V. 2004. Assessing the Impact of Health Management Approaches on System Total Cost of Ownership. *IEEE Aerospace Conference 2005*. March 5-12, Big Sky, Montana, USA

Ypma, A. (2001). *Learning Methods for Machine Vibration Analysis and Health Monitoring*. Doctoral dissertation. Technische Universiteit Delft, Delft, Netherlands

Zhang, X., Pisu, P. (2012). An Unscented Kalman Filter Based Approach for the Health-Monitoring and Prognostics of a Polymer Electrolyte Membrane Fuel Cell. *Annual Conference on Prognostics and Health Management 2012.* September 23-27, Minneapolis, Minnesota, USA

Zhu, J., Yoon, J.M., He, D., Qu, Y., Bechhoefer, E. (2013). Lubrication Oil Condition Monitoring and Remaining Useful Life Prediction with Particle Filtering. *International Journal of Prognostics and Health Management 2011*, vol. 4, Special Issue Wind Turbine PHM

BIOGRAPHIES

Heiko Mikat was born in Berlin, Germany, in 1979. He received his M.S. degree in aeronautical engineering from the Technical University of Berlin, Germany, in 2008. From 2006 he worked as trainee and later on as Systems Engineer at Rolls-Royce Deutschland, Berlin, Germany, designing and testing engine fuel system concepts and control laws. Since 2009 he works as Systems Engineer at the Airbus Defence & Space Supply & Propulsion Systems Department and is responsible for the development of new health management technologies for aircraft systems. His current research activities are mainly focussing on the maturation of failure detection and prediction capabilities for electrical, mechanical and hydraulic aircraft equipment.

Antonino M. Siddiolo was born in Agrigento, Italy, in 1976. He received his M.S. and Ph.D. degrees in mechanical engineering from the University of Palermo, Italy, in 2000 and 2006, respectively. From 2004 to 2005 he was a Visiting Scholar at the Centre for Imaging Research and Advanced Materials Characterization, Department of Physics, University of Windsor, Ontario (Canada). Then, he worked as a researcher and Professor at the University of Palermo and as a Mechatronic Engineer for Sintesi SpA, Modugno (Bari), Italy. Currently, he works as Systems Engineer at the Airbus Defence & Space Supply & Propulsion Systems Department, supporting the Integrated System Health Management project. His research activities and publications mainly concern non-contact optical three-dimensional measurements of objects and non-destructive ultrasonic evaluation of art-works. His main contributions are in the field of signal processing to decode fringe patterns and enhance the contrast of air-coupled ultrasonic images.

Matthias Buderath - Aeronautical Engineer with more than 25 years of experience in structural design, system engineering and product- and service support. Main expertise and competence is related to system integrity management, service solution architecture and integrated system health monitoring and management. Today he is head of technology development in Airbus Defence & Space. He is member of international Working Groups covering Through Life Cycle Management, Integrated System Health Management and Structural Health Management. He has published more than 50 papers in the field of Structural Health Management, Integrated Health Monitoring and Management, Structural Integrity Programme Management and Maintenance and Fleet Information Management Systems.