Virtual Framework for Validation and Verification of System Design Requirements to enable Condition Based Maintenance

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ABSTRACT

During the last decade Condition Based Maintenance [CBM] became an important area of interest to reduce maintenance and logistic delays related down times and improve system effectiveness. Reliable diagnostic and prognostic capabilities that can identify and predict incipient failures are required to enable such a maintenance concept. For a successful integration of CBM into a system, the challenge beyond the development of suitable algorithms and monitoring concepts is also to validate and verify the appropriate design requirements. To justify additional investments into such a design approach it is also important to understand the benefits of the CBM solution. Throughout this paper we will define a framework that can be used to support the Validation & Verification [V&V] process for a CBM system in a virtual environment. The proposed framework can be tailored to any type of system design. It will be shown that an implementation of failure prediction capabilities can significantly improve the desired system performance outcomes and reduce the risk for resource management; on the other hand an enhanced online monitoring system without prognostics has only a limited potential to ensure the return on investment for developing and integrating such technologies. A case study for a hydraulic pump module will be carried out to illustrate the concept.

1. INTRODUCTION

A maintenance strategy cannot change the reliability figures of a system design but an optimized concept can improve availability and reduce operation and support costs (Reimann, Kacprzynski, Cabral, and Marini, 2009). Three maintenance strategies and measures to overcome the issues associated with operating a system with non-infinite reliability can be distinguished.

Strategy / Measure	Run To Failure Mainten. [RTFM]	On Condition Maintenance [OCM]	Condition Based Maintenance [CBM]
Corrective Maintenance [CM]	General concept for RTFM	Failures which can cause neither a safety nor an economical critical event	Failures which can cause neither a safety nor an eco-nomical critical event. Requires online monitoring for fault isolation.
Preventive Maintenance [PvM]	Not included	Failures which are safety or economical critical. Fixed intervals to decide if a PvM is required.	Failures which are safety or eco-nomical critical w/o prognostics. Requires online monitoring to enable dynamic intervals for PvM.
Predictive Maintenance [PdM]	Not included	Not included	Failures which are safety or eco-nomical critical with monitoring and prognostics. Enables dynamic intervals to plan and perform PdM when required.

Table 1. Maintenance strategies and measures

A definition for the different concepts that will be used in the proposed framework is given in Table 1.

Standardized methods like Failure Mode Effects and Criticality Analysis (FMECA) or Common Mode Analysis are used to allocate probabilities and criticalities to each single failure mode in a system. The results are used to decide which failures are acceptable during operation and which ones have to be avoided through the introduction of a PvM or in case of a CBM concept, for which components it is expedient to develop capabilities to enable PdM. Monitoring or prediction methods to support the decision whether a PvM or PdM is required will always be imperfect. This will cause erroneous replacements of healthy components (known as No Fault Found [NFF]) and a waste of useful life by too early replacements of degrading components.

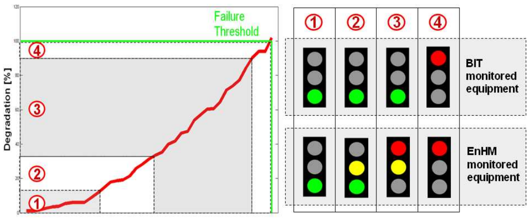

Figure 1. Enhanced Health Monitoring concept

Especially in the case of PdM, where a potential failure or degradation should be announced while the component still operates within the specified performance limits, the avoidance of NFFs and simultaneous realization of a high sensitivity to incipient failures is a challenge. For the realization of a dynamic scheduling of maintenance intervals, it is necessary to realize online condition monitoring to receive and process all information to decide when a PvM or PdM action is required. If the different components and the system itself are not designed to provide and process all required information, it is not possible to realize an optimized CBM concept (Dunsdon & Harrington, 2009). For this reason it is mandatory to establish all relevant requirements from the beginning of the system design phase. These requirements cannot be treated like general design requirements related to Maintainability or Testability aspects. Whereas a Build-In Test [BIT] can be specified through a fault isolation and NFF rate, a CBM system would also need the specification and verification of detecting failures before they occur and predicting future trends with a verifiable accuracy. The difference between BIT and an Enhanced Health Monitoring [EnHM] concept is illustrated in Figure 1.

Especially if the CBM system shall not only support the optimization of spares and personnel management but also be designed to shift scheduled intervals - which are important to ensure system safety aspects - into dynamic condition-based intervals, it is of high relevance to ensure traceability of how the CBM capabilities needs to be incorporated into the system design. Selected Key Performance Indicators [KPIs] can be defined to represent customer requirements or industrial interests. An understanding of how CBM affects these KPIs is needed to justify increased development and procurement costs plus a more complex system design.

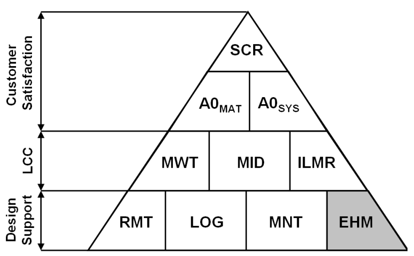

Figure 2. Hierarchical structure of the framework

The general hierarchical structure of how a Service Capability Rate [SCR] can be derived from the design and support elements of a system is shown in Figure 2. This architecture is used for the definition of the framework that will be described throughout this paper.

A SCR can vary from a success rate for performing reconnaissance missions in the field of the military aviation over transporting passengers or material for the civil sector to producing any type of goods in the industrial sector. The baseline parameters are Reliability, Maintainability and Testability [RMT], specifying how many and when any failure events are expected, how counter measures can be realized and which fault isolation capabilities are provided. The logistic concept [LOG] provides information on how resources like personnel, spares and consumables are supported. The maintenance strategy [MNT] specifies how the scheduled and unscheduled events are managed. The concept for Enhanced Health Management [EHM] has been introduced to specify the potential for the realization of CBM through EnHM and prognostics.

These baseline elements are considered as design and support elements of the system. The next level, as an outcome of the design and support level, is considered as Life Cycle Costs [LCC] related. The Mean Waiting Time [MWT] denotes how much time is lost due to waiting for missing resources; therefore it is related to periods during which the system cannot generate profit. The Maintenance Index [MID] indicates how much maintenance effort is required in Maintenance Man Hours [MMH] per Operational Hour [OH]. The Inverse Logistics Maintenance Ratio [ILMR] is used to quantify the amount of unscheduled events per OH, hence indicating the required capacity for spares to ensure the operational availability of the system. Based on these parameters and the system specific operational scenario, various KPIs can be derived. Important parameters are the operational availability of the material required to support the system for fulfilling its service aims [A_{0MAT}] and the operational availability of the system itself [A_{0SYS}]; these two parameters can be used to trace customer requirements and derive the SCR parameter. The required material can again be anything that is needed to support the system specific service task, like payload equipment for aircraft missions or industrial goods for production purposes.

The following sections will give an overview of a generic framework, addressing all above mentioned aspects by describing the conceptual design and purpose of the framework as well as basic assumptions and definitions.

The framework described on the following pages can be understood as a multifunctional environment, providing the capability to validate design and conceptual requirements as well as a tool for an integrated simulation concept of various modules composed to a complex system architecture for verification purposes. The general idea is shown in Figure 3.

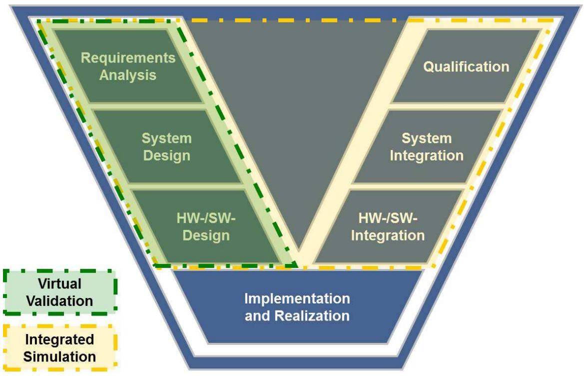

Figure 3. V-Model for framework applications

The modus as "Virtual Validation Environment" enables the derivation and validation of dedicated requirements for a system layout and EHM integration. Furthermore the "Integrated Simulation" modus supports model-based verification of KPIs and EHM requirements through the integration of validated simulation modules for diagnostics and prognostics on component or subsystem level.

To demonstrate the concept we will describe the simulation framework and conduct a case study. The case study will be carried out by showing how a simulation module for monitoring the status of a hydraulic pump could be integrated into the simulation environment and support the verification of RMT and EHM requirements.

2. Description of the Simulation Concept

The main aim of the work presented in this paper is to develop a simulation environment that can be used to perform trade-off studies for system design and maintenance concept aspects emphasizing the capability to include the evaluation of a CBM potential. As described in the introduction, we will distinguish between three different maintenance strategies and measures. As the framework has originally been developed to support aircraft design decisions, where - due to safety and economic reasons - RTFM shall be avoided, the RTFM strategy has been excluded. This assumption would also be valid for other complex or cost intensive applications like passenger transportation or industrial facilities. The decision tree which has been defined as basis for the framework is shown below.

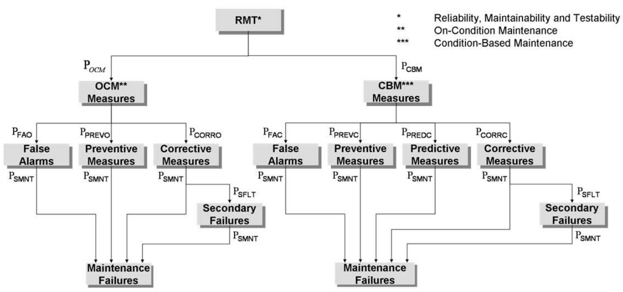

Figure 4. RMT, MNT and EHM Flowchart

2.1. Maintenance Parameters

According to the online monitoring capabilities, subsets of the primary failures specified by RMT will belong to the OCM or the CBM branch. A further partitioning into the different measures depends on the monitoring capabilities and definition of fixed maintenance intervals for inspection and overhaul. The probability that a failure belongs to one class is defined by the probability allocation parameter:

$$\mathrm{P}_j = \frac{\sum_j \lambda_j}{\sum_i \lambda_i} \tag{1}$$

In the case of P_{PREDC} (Predictive - CBM) the index j would denote all failure modes belonging to the class "Predictive Measures", while the index i would describe the sum of all failure modes belonging to the class "CBM Measures". It has been assumed that in excess of the primary failures classified by CM, PvM or PdM, each system also generates a number of false alarms (FA). As PvM and PdM would avoid the occurrence of a failure during service, the "Corrective Measures" are the only classes which generate additional secondary faults (SFLT) with the probability $\mathrm{P}_{\mathrm{SFLT}}$. For the overall simulation it should be considered that each maintenance action will also cause a secondary maintenance (SMNT) induced failure (defined by the probability P_{SMNT}). These maintenance induced failures can be mishandling, wrong installation or other secondary damages during overhaul and replacement or repair activities on the system (Byer, Hess, and Fila 2001). As each PvM and PdM should avoid the occurrence of a failure, it has to be performed before the failure happens. That means the introduction of such a measure would reduce the useful life of the system or component. This aspect has been introduced as additional probability for erroneous early replacements of the respective part. Due to the online monitoring of the CBM concept, this error will be lower for the PvM measures in the CBM branch than for those in the OCM part. Also it can be assumed that the evaluation of the information for PdM enables a much higher accuracy and confidence on estimating the optimum time to replace the monitored component than the monitoring without prognostics. Hence the waste of useful life for PdM can be considered to be lower than for PvM measures (Spare, 2001).

2.2. Reliability, Maintainability and Testability

The top level failure rate distribution is given by the RMT requirements as composition of all individual primary failure modes of the system. The probability for additional false alarms has been introduced as percentage false alarm rate for the respective class of events. It should be noted that - for maintainability aspects - each failure mode has been treated as individual event requiring a maintenance action. The maintainability aspect is described by the Mean Time To Repair for each individual failure mode $MTTR_i$.

Knowing the individual failure rates, a joint value on system level can be derived:

$$MTTR_{SYS} = \frac{\sum_i \lambda_i \cdot MTTR_i}{\sum_i \lambda_i} \tag{2}$$

A common approach for complex applications like aircrafts is to define a BIT failure isolation rate, specified through the capability to isolate single point failures to one or multiple root causes. It is assumed that CBM monitored components will have an ideal fault isolation capability, reducing the number of potential candidates for a single point failure to one single source. Considering this assumption and the fact that fault isolation for BIT monitored equipment has only to be performed once and the subsequent troubleshooting process for identifying the correct failure source would only include multiples of the replacement and checkout time for individual components, a formula for the resulting MTTR considering imperfect fault isolation can be derived (fdi: fault detection and isolation):

$$\begin{aligned} \Delta MTTR &= (P_{CORRO} \cdot \hat{p} + P_{PREVO}) \cdot P_{OCM} + P_{CBM} \cdot (1-\delta_{fdi}) \\ MTTR_{RES} &= \Delta MTTR \cdot MTTR_{SYS} \end{aligned} \tag{3}$$

with:

$$\hat{p} = p_{fdi_1} + \cdot(1-\delta_{fdi}) \cdot \sum_{k=2:n} (p_{fdi_k} - p_{fdi_{(k-1)}}) \cdot k + (1-p_{fdi_n})$$

where p_{fdik} indicates the probability to isolate a single point failure to $k = 2, \ldots n$ sources as testability requirement and δ_{fdi} as fraction of the replacement time required to perform the fault isolation. The imperfect BIT fault isolation will not only affect the repair time but also the resulting maintenance effort. Hence, calculation of the increased probability for maintenance induced failures in the corrective class of the OCM branch is implemented accordingly ($\delta_{fdi} = 0$):

$$P_{SMNT}(OCM_{CORR}) = P_{SMNT} \cdot \hat{p} \tag{4}$$

2.3. Logistic Parameters

The main parameter within the scope of a logistic concept for estimation of system availability is the mean delay time for unscheduled events. This value is composed of an administrative and a logistic delay [Mean Logistics Delay Time: MLDT] fraction giving an average parameter for the MWT. The MLDT parameter can be derived from the probability density estimate for the resulting failure rate of unscheduled events. Using these assumptions an estimate of the MLDT can be derived:

$$MLDT = \frac{\sum_{i=\lambda_s:\lambda_{max}} pdf(\lambda_{usi}) \cdot (\lambda_{usi} - \lambda_s) \cdot 0{,}5 \cdot T_{Lead}}{\sum_{i=1:\lambda_{max}} pdf(\lambda_{usi}) \cdot \lambda_{usi}} + T_0 \tag{5}$$

with (excluding secondary effects, which are added to receive the resulting unscheduled failure rate):

$$\lambda_{us} = \lambda_{Sys} \cdot [P_{OCM} \cdot (1+P_{FAO}) + P_{CBM} \cdot (P_{FAC} + P_{CORRC} + P_{PREVO})]$$

$$\lambda_{max} = \lambda(cdf(\lambda_{us}) = 1), \quad \lambda_s = pfr \cdot \lambda_{max}$$

and λ_{Sys} as overall system failure rate, λ_{us} as resulting failure rate for all unscheduled events, $pdf(\lambda_{us})$ / $cdf(\lambda_{us})$ as probability density / cumulative distribution function of λ_{us}, *pfr* as fill rate factor of spares in the operational scenario with $pfr = 1$ for $n_{Spares}(\lambda_{max})$, T_{Lead} as the maintenance related lead time (time between two spares deliveries or mean waiting time on maintenance specialists) and T_0 as the administrative delay time. Each element belonging to class other than PdM is treated as unscheduled event, while it is assumed that the capability to predict the occurrence of an event shifts it from being unscheduled to a scheduled maintenance. An arbitrary MLDT variation as a function of the spares fill rate is shown in Figure 5.

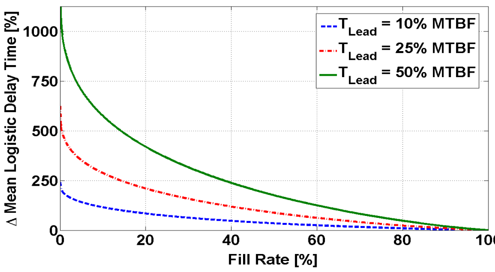

Figure 5. Mean Logistic Delay Time variation

The resulting MWT is the weighted average for scheduled and unscheduled events:

$$MWT = \frac{(\lambda_{Sys} - \lambda_{us}) \cdot T_0 + \lambda_{us} \cdot MLDT}{\lambda_{Sys}} \tag{6}$$

If PdM enables an accurate prediction of the time to failure, it can be assumed that the uncertainties for this class are reduced. This idea should reflect system operation without the need to consider a conservative assumption about the number of spares needed to maintain the system operational.

2.4. Enhanced Health Management Parameters

The EHM parameter set can be described through the values of P_{CBM}, P_{PREDC} and P_{FAC}. It should be noted that the framework implies that only an EHM monitored failure can also be predicted. It is also assumed that false alarms caused by other means of monitoring are ignored if the EHM algorithm for the respective failure mode does not confirm the failure. As EHM requires a deeper knowledge of the system it cannot be assumed that this approach works also in the opposite direction, ignoring a false alarm of an EHM monitored component if other monitoring features are not confirming the failure.

The accuracy of prediction has been identified as one key design parameter for the development of prognostic algorithms and concepts (Saxena, Roychoudhury, Celaya, Saha, Saha, and Goebel, 2010). The following assumptions have been made for the derivation of accuracy and precision; these will result in a probability for too early or missed replacements and can be used as requirements for the development of suitable algorithms:

- The prediction horizon has to ensure failures do not appear during the lead time. The lead time can be a time of continuous operation, the time interval between two spare deliveries or until maintenance specialists will be available.

- The prediction error ε is always a function of the prediction accuracy θ and the expected lead time T_{Lead}:

$$\varepsilon = \frac{1-\theta^2}{\theta^2} \cdot T_{Lead} \tag{7}$$

- The minimum required prediction horizon P_h is defined accordingly:

$$\mathrm{P}_h = \frac{1}{\theta^2} \cdot T_{Lead} \tag{8}$$

Assuming a fixed accuracy θ, it can be concluded that a replacement of the degrading component at $t_{Rep} = \theta \cdot t_{Pred}$ would avoid the failure with the probability specified by θ. Considering the mean and minima/maxima prediction regimes with an accuracy θ, the following relations for the respective waste of useful life E_{WULi} can be derived:

$$\begin{aligned} &\text{Conservative} && \mathrm{E}_{WULMax} = \varepsilon \\ &\text{Optimal} && \mathrm{E}_{WULMean} = \varepsilon \cdot \frac{1-\theta}{1-\theta^2} \\ &\text{Opportunistic} && \mathrm{E}_{WULMin} = \varepsilon \cdot \frac{1-(2-\theta)\cdot\theta}{1-\theta^2} \end{aligned} \tag{9}$$

Figure 6 depicts these regimes for θ = *90%*. Assuming the conservative situation that all regimes can occur with the same probability, it can be concluded that the average waste of useful life is equal to $E_{WUL} = E_{WULMean}$.

- The resulting waste of useful life due to predictive maintenance is a function of the respective failure rate:

$$\Delta\lambda_i = \mathrm{E}_{WULi} \cdot \lambda_i \tag{10}$$

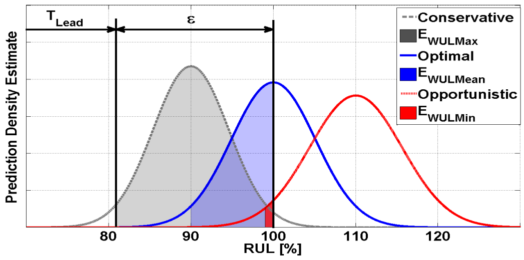

Figure 6. Prediction error regimes

2.5. Derivation of Performance Parameters

The system performance parameters can be derived according to Eq. (11), (12) (excluding scheduled overhauls):

$$A_{0i} = \frac{1}{1+\lambda_i \cdot (MTTR_i + MWT_i)} \tag{11}$$

$$SCR = A_{0MAT} \cdot A_{0SYS} \tag{12}$$

with λ_i as overall failure rate.

2.6. Uncertainty Representation

As the aim of this work was to develop a framework that has not to rely on pseudo-empirical simulation results, it was required to find closed form solutions for all stochastic processes that are used in the model. Therefore all distribution parameters like mean and variances have been propagated through the model by assuming stochastic independence for all single failure modes and a stochastic correlation of all failure modes that are interdependent.

Assuming weibull distributed time to failures with unitary shape parameter and therefore a constant failure rate (design and manufacturing processes should ensure constant failure rates but due to varying conditions and tolerances the results are usually distributed), we can derive the expression for the propagation of the uncorrelated parameters P_{UC} from class j belonging to branch i:

$$\mathrm{P}_{UCj} = \frac{\sum_j \lambda_j^{\,2}}{\sum_i \lambda_i^{\,2}} \tag{13}$$

The equivalent parameter for correlated events P_C can be derived as:

$$\mathrm{P}_{Cj} = \mathrm{P}_{UCi} \cdot \mathrm{P}_j^{\,2} \tag{14}$$

with P_j as the probability allocation parameter of event j caused by event i.

All primary failure rates can be treated as independent events with a covariance of $cov(z_i,z_j) \approx 0$. Only for merging the resulting primary with the secondary and maintenance induced failures, the respective covariances have to be taken into account. The secondary failures will only occur due to a primary failure belonging to the class “Corrective Measures”; a maintenance induced failure will only occur due to a previous event belonging to any class of the OCM or CBM branch. Moreover the relative increase in the failure rate of primary events will cause the same relative increase in the rate of secondary events. These relations motivated to imply a perfect linear correlation for these two scenarios to derive the respective covariance:

$$\operatorname{cov}(z_i, z_j) = \mathrm{P}_j \cdot Var(z_i) \tag{15}$$

with P_j as probability allocation parameter of event j caused by event i.

Well known laws for the calculation with stochastic variables have been used to propagate all mean and variance parameters through the system model (Elandt-Johnson & Johnson, 1980; Stuart & Ord, 1998; Blumenfeld, 2001).

By applying these rules, we obtain the resulting distribution functions that will be used to estimate the distributions for the parameters MWT, ILMR and MID. As the maintenance effort is independent from logistic delays, they are again treated as independent variables, providing the basis to calculate the resulting distributions of A_{0i}.

The specific distributions for the various parameters that have been used in the framework are listed in Table 2. Near real-time capable maximum likelihood estimators have been implemented into the simulation to estimate the distribution parameters by using the propagated expectation and variance of each stochastic variable as input.

Arbitrary simulations with random number distributions instead of the closed form solution for an OCM and CBM concept have been carried out to validate the concept. It can be seen that the results are sufficient accurate to assume the environment can be used to simulate processes with stochastic variables in a closed form solution (see Figure 7).

Failure rates:	Two-parametric weibull distribution with constant failure rate
False alarms:	Lognormal distribution
Prediction Error:	Lognormal distribution
MWT:	Lognormal distribution
MTTR:	Lognormal distribution
ILMR:	Two-parametric weibull distribution
MID:	Lognormal distribution
A_0:	Two-parametric weibull distribution

Table 2. Parameter distribution type

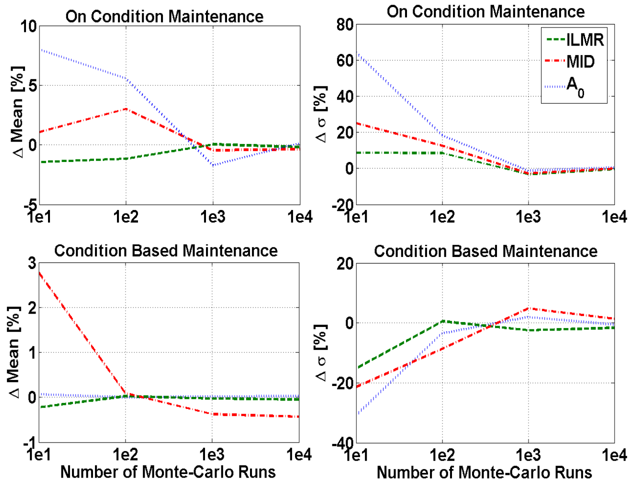

Figure 7. Monte-Carlo validation

3. Application as Virtual Validation Environment

The validation process is mainly based on a bottom-up and top-down justification and traceability analysis of all system design requirements. The idea for supporting this concept by utilizing the proposed framework is shown in Figure 8. The validation is performed by tracing all failure mode specific EHM requirements to the top level system requirements. The parameter CBMR comprises all EHM features. It is composed of the diagnostic [HMC] and the prognostic [FPC] part. Prognostic accuracy [PA], and prognostic coverage [PC] are used to describe the resulting FPC. The HMC is defined by the detection rate [DR] and false alarm rate [FAR]. The traceability to component level design requirements for hardware and software development is realized according to Eq. (2) by using the respective failure rates as weighting factors.

The following sections will give an overview of how a trade-off study could look like. A simplified cost-benefit approach will be discussed. More complex applications to find the optimum solution involving multiple cost functions will be the scope of future activities. Two arbitrary simulation runs have been conducted to illustrate and discuss the application as virtual validation environment. The first scenario simulates different design solutions for CBM without any PdM, only improving the fault isolation capabilities and conditional awareness of the system. The second scenario uses the same system design as baseline and evaluates a CBM concept with an integrated PdM capability, enabling the full potential of CBM.

This comparison should help to understand the impact of diagnostic and prognostic approaches on the three selected parameters SCR, MID and ILMR and if any saving potentials can be identified. It has to be noted that the results will vary if the logistic or maintainability parameters are modified; nevertheless the shown cases will provide sufficient information to discuss the main aspects. In the following discussion, the variance of each parameter can be understood as a factor describing the individual risk while the expectation value represents the potential to fulfil operational objectives.

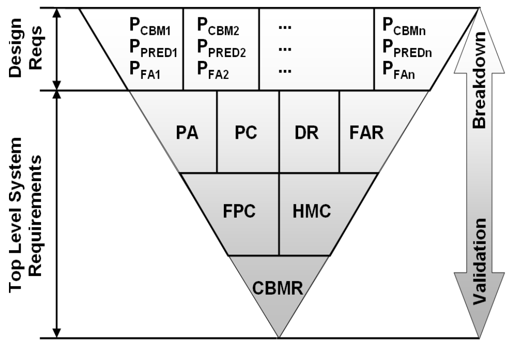

Figure 8. EHM validation

3.1. EHM without Prediction Capabilities

For this study, the parameter "CBM Capability" quantifies the online monitoring features without predicting any future trends. From the results presented in Figure 9 it can be seen that the implementation of EnHM without simultaneous development of prediction capabilities can mainly improve the MID, hence reducing the maintenance effort per OH. This observation can be explained with the improved fault isolation and optimized preventive maintenance due to the online monitoring capabilities of EHM. The reduction of MMH/OH will also ensure an improvement in the resulting SCR of the system; however since all failure events are still unscheduled, this improvement will not be the same as for a fully integrated CBM system with PdM. This effect can also be seen in the almost unaffected trend of ILMR. The minor improvement in ILMR is due to the reduced number of false alarms for a redundant monitoring concept using a fusion of BIT and EHM for status assessments and the optimized preventive maintenance methods.

As a result it can be concluded that enhanced diagnostics without prognostics will mainly reduce the maintenance effort expectation and variance. While the reduced expectation value corresponds to less maintenance activities per OH, indicates the reduced variance a potential for a better scheduling of resources and manpower. The increase in the SCR expectation is a side effect of the improvement seen in the MID.

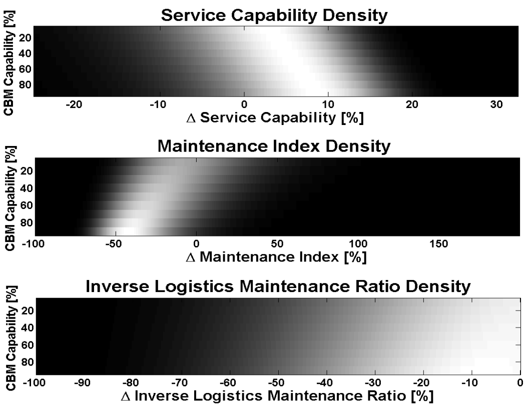

Figure 9. Sensitivity study EHM without PdM

3.2. EHM with Prediction Capabilities

By performing the same simulation as before with a CBM system including prediction capabilities for all monitored failure modes (now "CBM Capability" represents the quantity of failures that are monitored and can be predicted), the PdM concept reveals itself with its full potential. The implementation of prognostics has a significant impact on all three parameters by optimizing the expectation value and reducing the respective variance (see Figure 10).

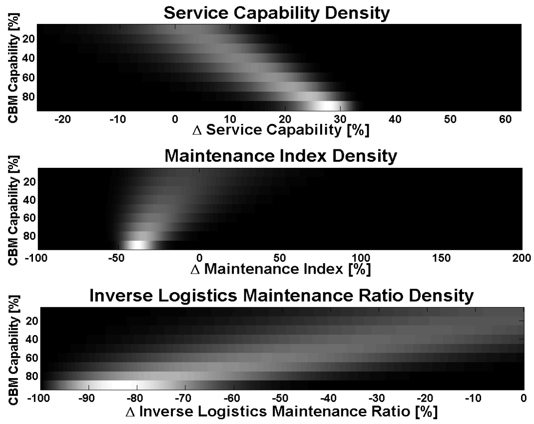

Figure 10. Sensitivity study EHM with PdM

The potential to move unscheduled events into a scheduled scenario, without the need to incorporate all uncertainties associated with a system that enters service, reduces the risk for all parameters.

The improved SCR expectation trend is mainly related to the avoidance of secondary failures, the reduced waste of useful life for PdM in comparison to PvM, the improvement for fault isolation of the predicted failures and the planning for a PdM measure before the failure occurs. The prediction of all events belonging to the class PdM has reduced the MWT to the fraction of the administrative delay time that is not allocated to the provision of spare parts and consumables. Simultaneously, the number of unscheduled events per OH is reduced, providing the potential to save costs for producing and storing spare parts before they are needed. The further improvement in the characteristics of the MID compared to the previous simulation without PdM can be explained with the reduction of the overall variance in the primary failure events and the avoidance of secondary failures by replacing the monitored item before a failure occurs.

3.3. Discussion of Results

By comparing the results for EHM with and without PdM it can be conducted that the enhanced health monitoring without prognosis may not compensate the investment needed for the development, production and operation of the health monitoring system. The minor improvement in the SCR due to the optimized trouble shooting process through online monitoring without reducing the risk, does not provide sufficient potential to reduce operational costs (e.g. less spares provisioning) without compromising customer requirements. Also the reduced MID cannot be seen as a savings potential, as the total number of people needed per operational site is defined through the number of people per maintenance action and the number of specialists per operating system. These people have to be paid, even if they have less work to do. The reduced variance is only an indicator that the risk for incorrect planning of maintenance resources is reduced. The more accurate PvM measures are expected to enable further improvement potential.

In contrast to the results for EHM without PdM it can be seen that the implementation of prognostics can help to reduce the overall risk for fulfilling service objectives. Simultaneously a reduction of the unscheduled events enables operation with less spares and the potential for a further simplification in the logistic concept with a reduced risk to compromise customer requirements. Therefore it can be concluded that the integration of an EHM system should aim for enhanced health monitoring and predictive capabilities, otherwise the return on investment for the integration of EHM cannot be guaranteed.

However, also for the EHM without prognosis it is possible to show the improvement potential and to use the proposed framework to derive requirements for the development of EHM functions. All resulting EHM requirements for diagnosis and prognosis are mainly quantified through the failure modes that can be monitored or predicted plus the accuracy and robustness of the respective algorithms.

3.4. Cost Benefit Analysis

This section should give an introduction of how a Cost-Benefit-Analysis can be carried out by utilizing the proposed framework. We will focus on a Performance-Based-Contract [PBC] scenario, where the system provider has to pay penalties if the operator cannot obtain the service aims (e.g. availability). A full blown Cost-Benefit-Analysis approach should be to find the global minimum of a function that takes the following cost elements into account:

i) CBM design and procurement costs;
ii) PBC penalties and rewards;
iii) Logistic cost elements;
iv) Spares and resources management cost elements.

By utilizing the framework a distribution function for each performance indicator can be derived. The parameter of interest for availability contracting would be A_0. By assuming reasonable cost functions for contractual penalties and operation and support cost (OSC) savings due to reduced spares provisioning by varying the fill rate, a minimum of the resulting cost function can be found.

An example plot for this scenario, assuming a contracted availability of 80% and deriving the delta costs by means of cost indexing, is shown in Figure 11. The allocation of the minimum resulting costs is determined by all design and support parameters. The risk to achieve this cost value can be quantified through the variance of each single parameter. By adding more cost functions to estimate the resulting operation and support costs, it is possible to find the optimum solution for an EHM design concept. The LCC simulation can either be used to identify an optimal EHM concept or to derive acceptable design cost values to satisfy a business case for a given operational scenario.

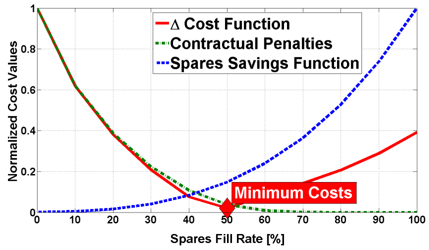

Figure 11. Cost functions for availability contracting

4. Use Case for Integrated Simulation Concept

In this section a case-study related to a generic hydraulic pump module will be presented: the aim is to further understand the concepts so far explained and to quantitatively show the improvements in the design phase that can result by utilizing the approach here illustrated.

After a brief introduction regarding the pump system and its main sub-components, the interest will be focused on the bearings, as sub-component of the pump system. In fact, care has been spent on properly simulate meaningful bearings' conditions, namely the behaviour of a bearing in presence of a defect and the degradation of the bearing behaviour following a growth in defect's severity. Both nominal and faulty behaviours have been validated by means of experimental tests. The model has been therefore used to test new diagnostic and prognostic algorithms; in fact, faults can be implemented under different operating conditions rather than waiting for these to occur. A generic approach has been followed to verify and validate the model creation and to properly assess effectiveness and efficiency of algorithms for diagnosis and prognosis: this approach is illustrated, as a flow chart, in Figure 12.

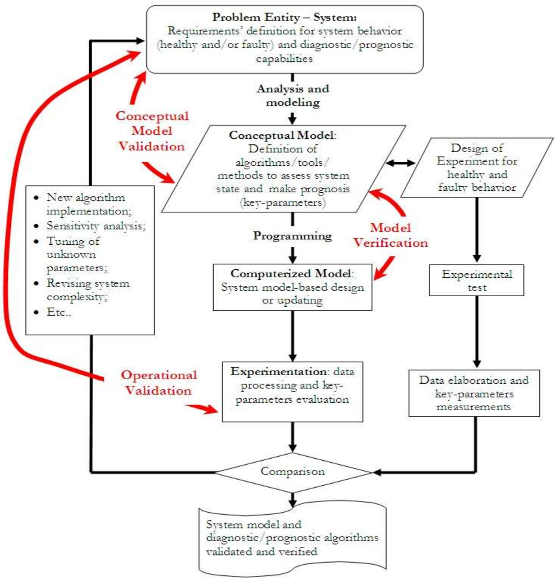

Figure 12. Flow chart of the EHM designing phases

The bearing dynamic model has been thereafter integrated in a general simulation pump framework that has been designed on purpose. The framework allows one to simulate the behaviour of a generic pump - within its sub-components – together with different monitoring capabilities on the various components: this way the use of the framework as a valuable tool for requirements' verification will be demonstrated, as well as the capabilities of the framework itself of assessing variation in system's performances when varying monitoring concepts.

4.1. Hydraulic Pump System

The hydraulic pump object of our interest is a variable displacement, axial piston pump. The most important groups are the Drive Group, the Displacement Group and the Control Valve Group. The Drive Group is the functional hearth of the system since it contains the axial pistons in the cylinder block and the control plate. The basis of the pump is an assembly of precision machined, high strength steel parts for the rotational functional parts, mounted in an alloy case. The main shaft is supported in rolling elements bearings. Pump sealing is achieved using either O-Rings or a mechanical seal. In Figure 13, a scheme is shown displaying the main actors of the system under investigation: in particular, one can recognize the metrological solutions that will characterize the enhanced monitoring capabilities of the system, namely a system of bi-axial accelerometers (to measure two orthogonal accelerations along the plane on which every roller bearing lies) and an electric chip detector to evaluate the level of contaminant in the hydraulic circuit.

There is a large number of items within the pump that will result on a system failure. Some of the pump's failures are direct consequence of the part failures (for example shear of the shaft); some others are indirect, e.g. debris in the hydraulic circuit. In the final simulation that will be performed, the failure of four pump sub-components will be considered, namely: bearings, sealing, shaft and pistons.

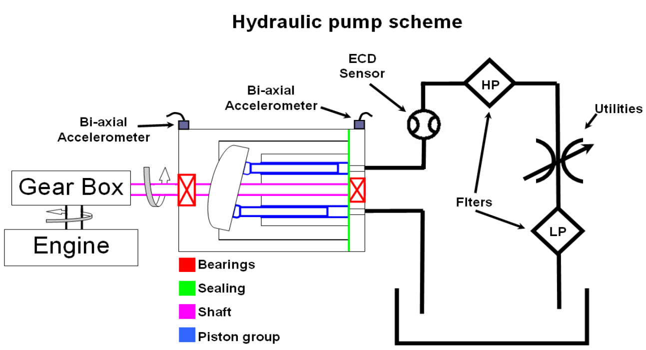

Figure 13. Hydraulic Pump scheme – The sub-components that will be the actors of the simulation are highlighted

The dynamic model of the first sub-component (the roller bearings) will be briefly presented in the next section.

4.2. Dynamic Model of Roller Bearings

In a bearings system, the time-variant characteristics are the result of the orbital motion of the rolling elements, whilst the non-linearity arises from effects due to the Hertzian force-deformation relationship. The model here presented and utilized is based on the work carried out by Sawalhi and Randall (2008). The main fundamental components of a rolling bearing are: the inner race, the outer race, the cage and the rolling elements. Moreover, important geometrical parameters are: the number of rolling elements n_b, the element diameter D_b, the pitch diameter D_p and the contact angle α (see Figure 14). The non-linear forces between the different elements, the time-varying stiffness, the clearance between rolling elements and races have been implemented into the model. The bearing has been modeled as a five Degrees of Freedom (DoF) system: two orthogonal DoF belong to the inner race/rotor component (x_i and y_i), two DoF are related to the pedestal/outer race (x_o and y_o) and the last one (y_r) has been added to match the usually high frequency bearing response (16 kHz with 5% damping). Mass and stiffness of the outer race/pedestal on the other hand have been adjusted to match a low natural frequency of the system. Finally, mass and inertia of rolling elements are ignored.

The non-linear and time-variant model has been further detailed regarding its capabilities in reproducing health and faulty behaviours. These refinements are related to: a) random fluctuation of inner and outer race profiles; b) forces generated as a consequence of the roller element impact with the resulting profiles roughness; c) Elasto-hydrodynamic lubrication; d) slippage; e) mass unbalances and f) presence of spalling in the outer and inner race-way.

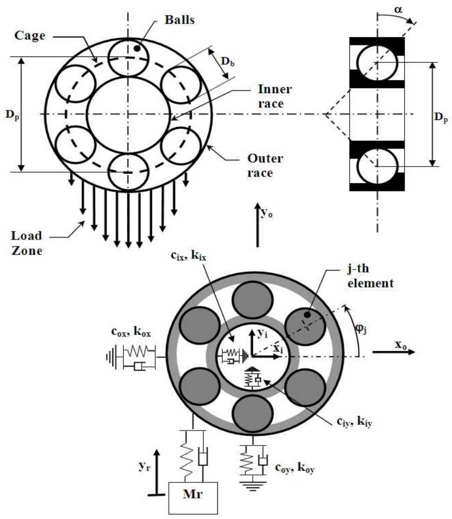

Figure 14. Roller bearing geometry and physics modeling scheme

As illustrated in the flow-chart of Figure 12, the verification and validation approach follows a circular and continuous path among the conceptual model validation, the computerized model verification and the operational validation. The conceptual model validation refers to the problem of determining that concepts, theories and assumptions underlying the conceptual model are correct; whilst the model verification is defined as assuring that the computer programming and implementation of the conceptual model is correct. On the other hand, the operational validation is defined as determining that the model's output behaviour has sufficient accuracy for the model's intended purpose. In the case under investigation, the domain of the model's intended applicability is wide, since both nominal and faulty behaviours have to be properly simulated. Moreover, the same approach has been followed to verify and validate algorithms for diagnostics and prognostics. In the end, if suitable diagnostic and prognostic concepts could be defined and successfully tested, it is possible to integrate the validated simulation modules into a general simulation framework in order to assess, evaluate and validate the performances of the system resulting from the integration of modules with EHM capabilities.

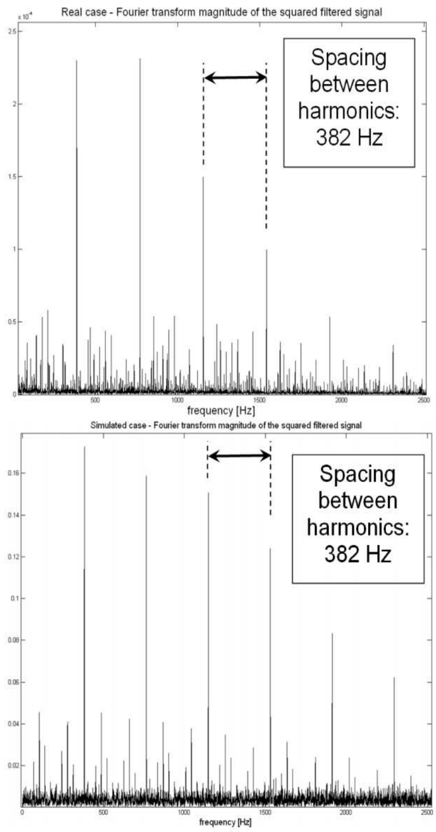

Figure 15. Envelope of the two signals used to detect the frequency-value of encoded impulsive transients

Several experimental tests have been conducted in order to validate the system. The iterative analysis of the experimental findings related to both nominal and faulty behaviors has allowed the continuous and better matching of the computerized model to reality (model validation). A challenge was the correct simulation of a defective bearing, the developing of tools to diagnose a defective behavior and the implementation of concepts for Remaining Useful Life [RUL] prediction.

Various kinds of defect have been simulated in real bearings, as – for example - spalls of different length and depth both in the inner and outer race. Common tools in the frequency domain can be used for the validation behaviour of baseline conditions; this is not generally true for faulty conditions. As a matter of fact, together with a simple monitoring of the quadratic mean of the acceleration, a data driven diagnostic approach has been implemented for the present study; experimental data have been used to train a neural network for defect detection and classification. The diagnostic approach has moreover been made more robust by the integration of a mathematical tool named Spectral Kurtosis (Antoni, 2004): this instrument gives the possibility to have an estimation of the band to be demodulated without the need of historical data. In Figure 15, a comparison is shown between the signals processing of the vertical acceleration measured on the pedestal of a faulty bearing and the analogous results gained by running a simulation of its computerized model: the Fourier transform magnitude of the squared filtered signals clearly shows the typical faulty frequencies of the bearing (given the bearing characteristics, a theoretical Ball Pass Frequency Outer race of 382.3 Hz was calculated) as spacing between harmonics both in the real (upper trend) and simulated (lower trend) results. In the end of the designing phase, a verified and validated dynamic model has been released. It has been therefore widely used to test new diagnostic and prognostic algorithms since the required diagnostic features can directly be derived from simulated signal pattern.

However, the development of suitable prognostic algorithms needs also to focus on the evaluation and prediction of trends or degradation paths. Hence it is necessary to further develop degradation models that can be used to simulate growing faults. The derivation of such models is not always straightforward, as the process of degradation is stochastic and does not always follow known parametric laws (Bechhoefer, 2008). Several model-based approaches have been adopted so far for failure prognosis (Orchard, 2007); among the various methodologies implemented, the most promising mathematical framework is the one based on Particle-Filtering. This approach allows handling nonlinear, non-Gaussian systems; it assumes: a) the definition of a set of fault indicators, for monitoring purposes, b) the availability of real-time process measurements and c) the existence of empirical knowledge to characterize both nominal and abnormal operating conditions.

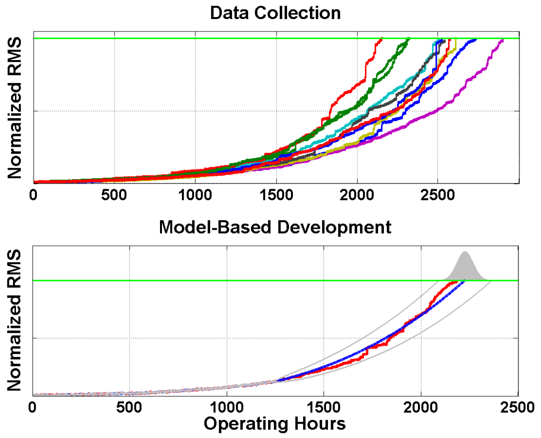

Figure 16. Model-based development of prognostic algorithms

Therefore, by means of this approach the current state estimates are in real-time updated and the algorithm predicts the evolution in time of the fault-indicators, providing the pdf of the RUL. Following the same verification and validation approach, the prediction algorithm has been designed. In Figure 16, one can see (upper graph) the process of validating the algorithm by running different simulations assuming representative degradation paths; in the lower graph, an example plot for a model-based RUL estimation is displayed.

The verified and validated model (regarding both its physical behaviour and the diagnostics and prognostics algorithms) has been therefore integrated into a simulation module, which will mimic the behaviour of a complex system. The model will be presented in the next section.

4.3. Hydraulic Pump Simulation

The simulation will regard four sub-components of the hydraulic pump, namely the sealing system (SEAL), the shaft (SHAF), the roller bearings (BEAR) and the piston-group (PIST). FMECA documents have been looked up in order to set realistic ratios between the values for the failure rates. Aim of the current simulation is to show and demonstrate how the developed framework can be usefully and effectively utilized in order to verify the fulfilments of the top-levels requirements.

Bearings models characterized by the enhanced diagnostic and prognostic capabilities just discussed have been integrated into the simulation framework; the system has been virtually equipped with accelerometers (see Figure 13) so that the health-state of the bearings system can be continuously checked. Then, as soon as a deviation from the baseline state is detected by the diagnostic algorithms, prognostic tools will process the acquired data and communicate the central processing and control unit estimated RULs and confidence levels. This will then affect the performances of the overall system and the framework so far discussed will be therefore utilized to quantitatively assess the performances' variations by using the indexes already discussed in the previous sections. In other words, the primary results of the current simulation will be the failure rate distributions of the system; these will be fed to the virtual framework to derive the performance indexes and hence values directly related to customer satisfaction.

To handle a more realistic and complex scenario, the hydraulic system has been further virtually instrumented with an Electric Chip Detector (ECD – see Figure 13). This sensor measures in real time the amount of debris and contamination of the hydraulic liquid; this way, a preventive maintenance approach can be implemented for the piston group and the bearing system in the CBM branch. The bearing diagnostic algorithm can in fact be also used as fault confirmation for preventive actions on the pistons group.

Finally, the other components are considered to be classically monitored by means of an "On Condition Maintenance" approach, which results in corrective and preventive maintenance.

Hence, according to the on-line monitoring capabilities just introduced, the simplified simulation scheme in Figure 17 can be shown: it defines the primary failures that will belong to the OCM branch and the ones that will belong to the CBM branch.

In the following Figure 18, a diagram explaining the flow of the information in the verification procedure just presented is displayed. At the bottom of the graph lies the hydraulic pump model with its integrated enhanced monitoring concepts related to the bearing system. By assuming failure rate distributions for the different components, the simulation will randomly generate events; these will be treated accordingly to the system specifications and so the probability classes already shown in Figure 17 will be populated.

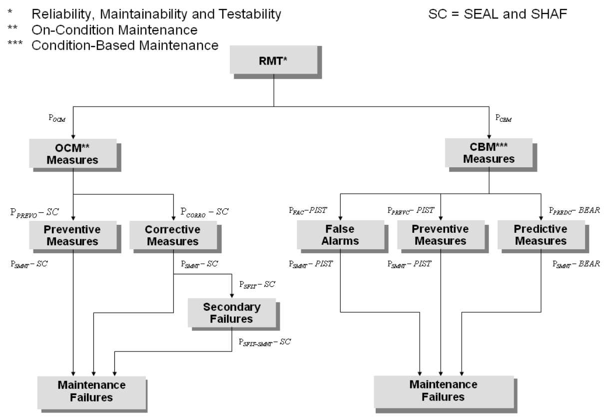

Figure 17. Maintenance approach hydraulic pump system

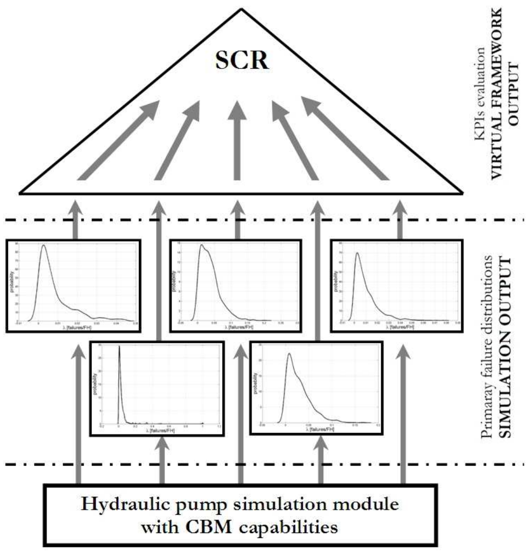

Figure 18. Verification process of a hydraulic pump module

Therefore, the statistical parameters (mean and variance) of each failure mode can be calculated and, by using the virtual framework, they can also be easily propagated in order to get the distributions of the performance indexes: availability, maintenance index and inverse logistics maintenance ratio.

Verification of the EHM design requirements can be carried out by comparing the results of the validation phase with the distributions from the verification phase. The resulting error in the system performance parameters can be used to assess whether the design goals are met or not. Based on this assessment it can be decided whether the EHM concept needs to be revised or can be implemented. The results for the selected use case are shown in Figure 19.

The shown use case simplifies the system architecture to a single component. The same approach can be applied if the integration would cover multiple components and subsystems with individual failure modes.

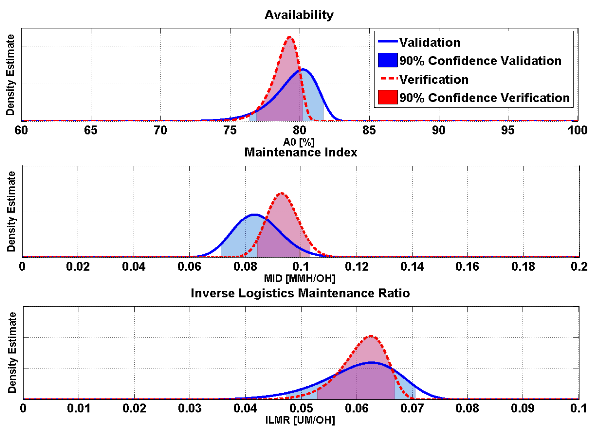

Figure 19. Performance indexes simulation case study

5. Conclusions

The proposed framework can support the development of a CBM system by validating diagnostic and prognostic design requirements w.r.t. selected KPIs or customer requirements. Sensitivity studies revealed that a CBM system should aim for the integration of predictive capabilities, as the improvement potential for an online monitoring system without prognostics is limited to a reduced maintenance effort and minor improvements in availability or other performance parameters of the system.

The concept provides a simple but robust approach for trade-off studies during an early design stage. Further improvements of the framework will focus on the evaluation and integration of a generalized weibull correlation coefficient (Yacoub et al., 2005) to replace the assumption for linearity between primary and secondary effects. The next step for maturation will be to validate the concept with established simulation tools (e.g. Simlox) for spares and resource management.

The idea for an integration of cost estimations and optimizations has been discussed. Follow-up studies to derive cost functions with established LCC estimation tools (e.g. PRICE) will be carried out. The integration of authoritative cost functions to obtain a framework for a multidimensional optimization of costs related to EHM design parameters, PBC aspects as well as resources and logistics management will be the main scope for future activities.

The concept for model-based verification of top-level system requirements has been illustrated. This approach shall enable the evaluation and assessment of diagnostic and prognostic capabilities before the system enters service. The authors are convinced that the cost-efficient validation and verification of multiple monitoring and prediction functions composed to a complex system design can only be realized in a virtual environment. The proposed framework provides such an environment and will be further maturated to support the V&V process for the development of a CBM system.

NOMENCLATURE

Symbols

ε	*Prediction Error*
θ	*Prediction Accuracy*
λ	*Failure Rate*
σ	*Standard Deviation*

Abbreviations

A_0	Availability
BIT	Build-In Test
cdf	Cumulative Distribution Function
CBM	Condition Based Maintenance
CM	Corrective Maintenance
DoF	Degrees of Freedom
DR	Detection Rate
ECD	Electric Chip Detector
EHM	Enhanced Health Management
EnHM	Enhanced Health Monitoring
FA	False Alarm
FAR	False Alarm Rate
FPC	Failure Prognosis Capability
FMECA	Failure Mode Effects and Criticality Analysis
HMC	Health Monitoring Capability
ILMR	Inverse Logistics Maintenance Ratio
KPI	Key Performance Indicator
LCC	Life Cycle Costs
LOG	Logistics
MMH	Maintenance Man Hours
MNT	Maintenance
MTTR	Mean Time To Repair
MID	Maintenance Index
MWT	Mean Waiting Time
MLDT	Mean Logistics Delay Time
NFF	No Fault Found
OCM	On Condition Maintenance
OH	Operational Hours
OSC	Operation and Support Cost
PA	Prognostic Accuracy
PBC	Performance Based Contract
PC	Prognostic Coverage
pdf	Probability Density Function
PdM	Predictive Maintenance
pfr	Spares Fill Rate
PvM	Preventive Maintenance
RTFM	Run To Failure Maintenance
RMT	Reliability, Maintainability and Testability
RUL	Remaining Useful Life
SCR	Service Capability Rate
SFLT	Secondary Faults
SMNT	Secondary Maintenance
V&V	Validation & Verification

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BIOGRAPHIES

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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 CASSIDIAN Supply Systems Department, supporting the Integrated System Health Monitoring (ISHM) 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.

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