Framework for a Uniform Description of Prognostics and Health Management

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ABSTRACT

The successful application of Prognostics and Health Management (PHM) systems is increasing steadily worldwide. One reason for this is the increasing number of smart products entering the market. Mirroring smart products, PHM systems are now developed and applied in a variety of engineering disciplines, all using different models and methods. Model, method, and product type diversity all lead to highly complex systems. To handle the complexity in an efficient way, this paper introduces a common base for PHM systems, in the form of a framework – the goal being a generic model with clear formalization of both notation and semantics. Accordingly, the PHM System is separated into both a RUL-Health model and a context model. Both are described and connected through a roles and relation model of their modules. Diagnosis and prognosis modules – estimating the components' health using lifetime models – are RUL-Health based. For a holistic description, the general lifetime model (GLM) is introduced. This allows different measures of component health to be represented in a single model and reduces the complexity to two metrics – remaining useful life (RUL) and health index (HI). These metrics – combined with internal/external requirements & targets – are the input for the context modules' optimization and decision making.

1. INTRODUCTION

Due to an increase in smart products, the successful application of Prognostics and Health Management (PHM) systems is steadily increasing. The obvious benefits are increased safety and reliability, complemented by reductions in damage, cost and servicing. To sum up, PHM is gaining ground as a technical domain and provides huge benefits. Despite this, a meta-level structure for the arrangement, comparison, definition, and distinction of PHM from reliability engineering and other disciplines remains absent (Celaya Galván 2014). For this purpose, a uniform description of PHM with a generic framework and a clear formalization is presented in this paper.

The Term "Prognostics and Health Management" itself is defined by several authors in several ways. For example, Celaya Galván (2014) defines PHM in terms of the main target as the "estimation of remaining useful life of a component". Coble (2012) focuses more on the elements of PHM – "full PHM Systems typically include […] data collection, fault diagnostics, system prognostics, and planning". Fries (2014) adds the condition that PHM is applied to the current life-cycle.

This paper sees the in-situ use of PHM during the components life cycle as a crucial point in the distinction of PHM from other disciplines. It is also distinguished by its nature of concerning component health management and decisions in addition to observation. The following provides a universal description:

Prognostics and Health Management assesses remaining useful life in situ to manage component health and derive decisions.

At this point, the definition of remaining useful life (RUL) is adopted from the work of Celaya Galván (2014), which cites it as "the amount of lifetime a component can be expected to continue operating within the stated specifications given". In contrast with Celaya Galván (2014), the more general term of lifetime is used in place of time. Henceforth, the RUL definition t_{RUL} will be distinguished from time to failure t_{TTF} by the start and end point, presented in figure 1.

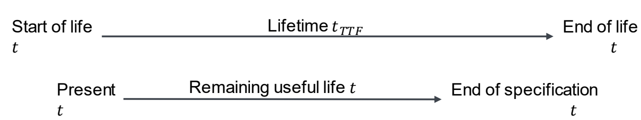

Figure 1. Remaining useful life and time to failure.

The second characteristic value is component health, as expressed by the health index (HI). This metric describes the general decrease in health of the component over its lifetime, illustrated in figure 2 (healing effects → HI increase). Wang (2012) distinguishes between a physics health index (PHI) and a synthesized health index (SHI). The PHI is applicable if one signal correlates with physics of failure (PoF) metrics. If there is no dominant PoF observed, the SHI overcomes the difficulty by deriving a one dimensional health index from a multi-dimensional signal.

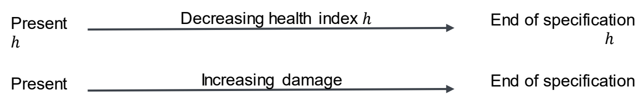

Figure 2. Health index and damage.

Figure 2 also demonstrates the negative correlation between health and damage. Attention is brought to this, as many lifetime models are based on degradation – defined as the component's damage path (Hines 2008). Irrespective of whether one tracks health or degradation, the end of specification is reached when the first failure criterion Z is crossed. All points will be discussed in detail in chapter 2.1.1.

2. PHM SYSTEM

The superordinate PHM System is modeled with its main elements and their interactions in figure 3.

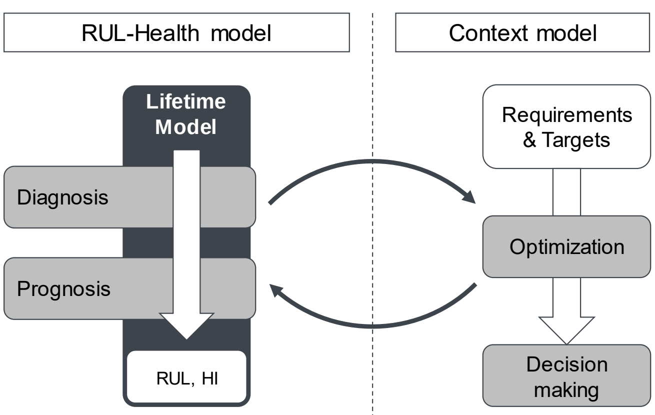

Figure 3. PHM System.

The System is divided into both the RUL-Health model (component based) and the context model. Light grey elements are modules representing mathematical methods. Within the RUL-Health model, the general lifetime model and the diagnosis and prognosis modules assess in-situ RUL and HI. The context model is based on internal/external requirements & targets. An optimization is applied between the models and forms the base for decision making. It is important to note that the models presented confer a holistic and generic perspective. Individual PHM Systems are not mandatory considering every model element.

2.1. RUL-Health Model

The RUL-Health model is separated into both the general lifetime model (GLM) and the diagnosis and prognosis modules. Generally, a PHM system is regarded as a combination of several lifetime models (Fries 2014). Where there are n different lifetime models describing the components' health, there are n RUL-Health models as well. These single RUL-Health models can be combined under the V-Model (figure 4), which takes unequal prognosis results and uncertainties into account.

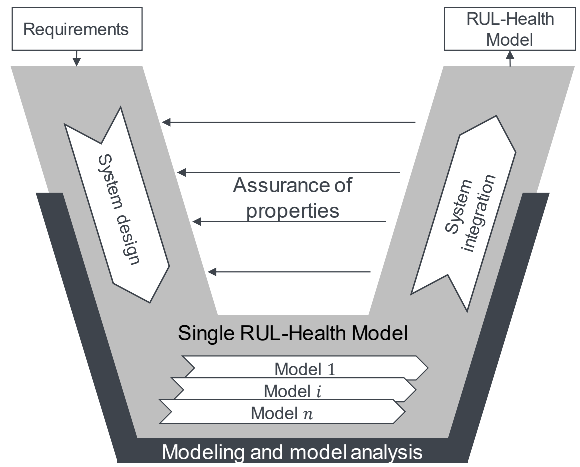

Figure 4. V-Model based on VDI (2004).

2.1.1. General Lifetime Model (GLM)

The general lifetime model is introduced to describe the HI over lifetime in a holistic form (figure 5). It enables the representation of degradation and failure probabilistic in a single model. As discussed in chapter 1, degradation correlates with the component health index H and the EOS is reached by crossing the first failure criterion Z. Each metric is connected to an inherent probability P, represented in GLM through the density function f. Beside the lifetime $t \in T$, the following notation is also used (Eq. 1 – 4).

$$H(T, P_H), \qquad h \in H \qquad (1)$$

$$Z(T, H, P_Z), \qquad \zeta \in Z \qquad (2)$$

$$f(T, H, \alpha_f) \qquad (3)$$

$$P(T, H) = \int\int f(T, H)\, dT dH \qquad (4)$$

Note that the density function is also connected to a significance level α (Bertsche 2008). At this point, figure 5 is reduced to only one failure criterion Z and two density visualizations, one over lifetime and one over H.

A major difference between degradation and failure probabilistics is that random failures cannot be traced by degradation (Meeker 1998, Bertsche 2008). Conversely, in classical failure probabilistics, knowledge concerning the trace of the components health is absent. This generally leads to higher uncertainty.

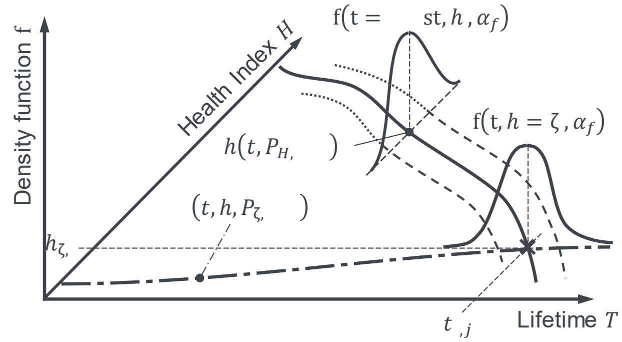

Figure 5. General lifetime model.

Usual lifetime models are covered in the GLM by reducing an axis, or by keeping one parameter constant. For example, the Weibull failure probability can be expressed by the integral over the density function at the crossing point of the health and failure criterion $\mathrm{f}(\mathrm{t}, h = \zeta, \alpha_f)$. Classic degradation models are reduced to the axes health index and lifetime. A comprehensive overview of lifetime estimation approaches is provided by Ahmadzadeh (2013), who distinguishes between physics based, empirical based, data driven and hybrid approaches. These classifications – combined with the scope of component characteristic and variation (uncertainties) knowledge – define the PHM system's area of application.

2.1.2. Modules

The diagnosis and prognosis modules are the interface between component and GLM. Similar to common understanding, time is divided into past (diagnosis t_{i-}), present ($t_i = t_p$) and future (diagnosis t_{i+}). Bachleitner (2016) defines the present as a model of reality, the past as the remembered present, and the future as the forward projected past. This philosophical perspective already demonstrates the inherence of uncertainties.

The role of diagnosis is to interpolate the component measurements $\varphi \in \phi$ in the general lifetime model. By comparison, the role of prognosis is to extrapolate the data from diagnosis. To ensure accurate extrapolations, it is necessary to know anticipated future operating conditions. These conditions are defined by the context as requirements & targets primarily of the component (internal $\theta_I \in \Theta_I$), and secondarily of the network the component is embedded in (external $\theta_E \in \Theta_E$). To exemplify this, Celaya Galván (2014) lists the current health status (RUL, HI) and anticipated future operating conditions as input commands, environments, and loads. The roles and interactions of diagnosis and prognosis between each other and the GLM is shown in figure 6.

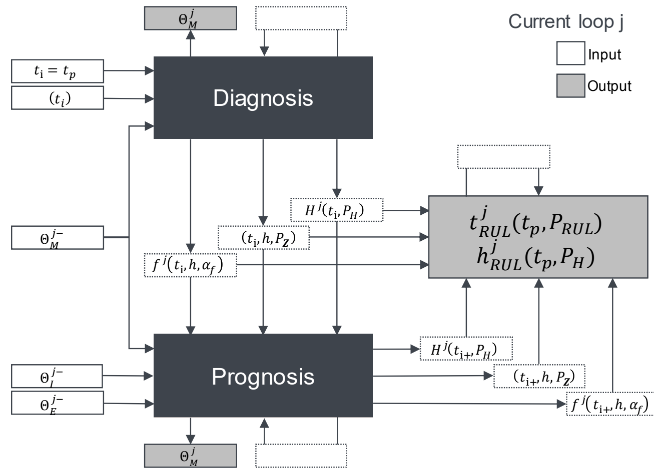

Figure 6. Roles and relation model – RUL-Health modules.

Each module will be executed for at least one loop j every lifetime step i. Note that prognosis and optimization results base on requirements and targets from the previous loop $j-1$. Beside the inputs and outputs already mentioned, there is additional meta data $\theta_M \in \Theta_M$ which addresses training and validation especially.

2.2. Context

A core aim of PHM systems is to manage component health, and to derive decisions. This is addressed in the context model. In chapter 2.1.2, internal/external requirements and targets are introduced as context inputs. The modules are optimization and decision making, whose roles and relations are shown in figure 7. Note that for combinatorial optimization a decision problem is corresponding.

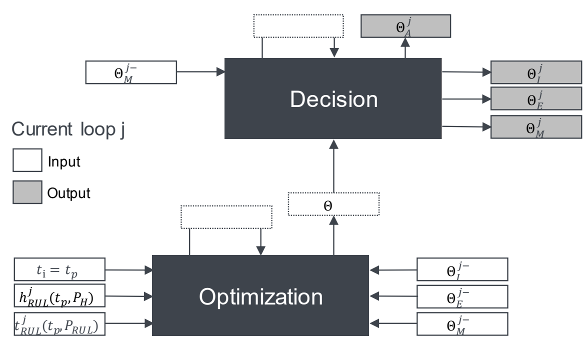

Figure 7. Roles and relation model – context modules.

In order to find the optimum RUL and HI, whilst taking the context into account, a multi-criteria optimization problem must be solved. In the process of decision making, an action ($\theta_A \in \Theta_A$), is performed, something not necessarily required in each loop. Each decision requires the associated risk and model uncertainty to be taken into account (Saxena 2010).

2.3. Uncertainty Propagation Map

Hines (2008) states that "since the lifetime cannot be precisely predicted, a probability distribution results". Beforehand, uncertainty was addressed in the GLM by the density function over health and lifetime. Both the meaning and sources of uncertainties are explored in this chapter. Sources of uncertainty are defined as modeling uncertainties (epistemic), input data uncertainties (aleatoric), measurement uncertainties (prejudicial) and operating environment uncertainties (combination) (Saxena 2010).

To ascertain the uncertainty of a chain of variances, the variance sum law can be applied (JCGM 2008). For independent variances, equation 5 can be used. For dependent variances, the covariance (equation 6) must also be taken into account.

$$Var\left(\sum_{i=1}^{N} a_i X_i\right) = \sum_{i=1}^{N} a_i^2 Var(X_i) \qquad (5)$$

$$+2\sum_{1\le i<j\le N} a_i a_j Cov(X_i, X_j) \qquad (6)$$

In diagnosis, uncertainties lie in component measurement, GLM modeling and diagnosis modeling. In prognosis, uncertainties lie in diagnosis, GLM modeling and prognosis modeling. Decision uncertainties include both diagnosis and prognosis input uncertainties, as well as modeling uncertainties of optimization and decision. According to the variance sum law, t_{RUL} can be described by equations 7–8 under the condition of independent variances.

$$E(t_{RUL}) = E(t_{EOS}) - E(t_p) \qquad (7)$$

$$Var(t_{RUL}) = Var(t_{EOS}), Var(t_p) = 0 \qquad (8)$$

h_{RUL} may be determined in the same way (equations 9–10).

$$E(h_{RUL}) = E(\zeta_{EOS}) - E(h_p) \qquad (9)$$

$$Var(h_{RUL}) = Var(h_p), Var(\zeta_{EOS}) = 0 \qquad (10)$$

By comparison, $Var(t_{RUL})$ depends on the prognosis variance and $Var(h_{RUL})$ on the diagnosis variance. Due to the inherence of diagnosis variance in prognoses, this follows $Var(h_{RUL}) \le Var(t_{RUL})$.

3. CONCLUSION

Uncertainties are directly connected with both risk and reward, and the extent of uncertainty defines the extent to which PHM systems may reasonably be applied. Furthermore, this paper demonstrates that PHM is distinct from other disciplines by shifting the designer influence into the life-cycle usage phase. This is specifically achieved through in-situ optimization and decision making, based on the RUL, HI, and all-important context. A clear separation between the lifetime model and modules (mathematical methods), as well as between the RUL-Health and context models enable a holistic and universal definition of PHM. This provides a basis to pursue further findings concerning PHM systems.

NOMENCLATURE

f	Density function
H, h	Health index
i	*index*
j	*loop*
P	Probability
T, t	Lifetime
α	Significance level
Z, ζ	Failure criterion
Θ_A, θ_A	Action data
Θ_E, θ_E	External requirements and targets
Θ_I, θ_I	Internal requirements and targets
Θ_M, θ_M	Meta data
Θ_O, θ	Optimization data
ϕ, φ	Component measurements

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BIOGRAPHIES

Mark Henss studied Mechanical Engineering at the Univ. of Stuttgart in Germany and received his academic degree M.Sc. in 2015. In the same year he started his work as a Research Assistant in Reliability Engineering at the Institute of Machine Components (Univ. of Stuttgart) and pursues his PhD studies.

Peter Zeiler studied Mechatronics at the University of Applied Sciences in Esslingen and Mechanical Engineering at the University of Stuttgart in Germany and graduated with the academic degree "Dipl.-Ing." in 2001. From 2001-2004, he was a Research Assistant in Reliability Engineering at the Institute of Machine Components, University of Stuttgart. He was awarded the academic degree „Dr.-Ing." from the University of Stuttgart in 2006. From 2004-2012 he was working as a team leader in the development of fuel injection systems at the Robert Bosch GmbH in Stuttgart, Germany. From 2012-2017 he was head of the departments Reliability Engineering and Drive Technology at the Institute of Machine Components, University of Stuttgart. Since 2017 he has been Professor at the Faculty of Mechatronics and Electrical Engineering at the Hochschule Esslingen, a University of Applied Sciences. His research interests are focusing on modelling and simulation of reliability as well as prognostics and health management. He is a member of the Advisory Board "Safety and Reliability" of the Association of German Engineers (VDI) and the working group "Reliability of Mechatronic and Adaptronic Systems" of the German Association for Materials Research and Testing (DVM).

Bernd Bertsche began his professional career at Daimler AG in Stuttgart from 1989-1992. He has been a Professor of Mechanical Engineering at the Institute of Machine Components at the Univ of Stuttgart, as well as the Head of the Reliability Engineering Department since 1996. In 2001 he became Head of the Institute, as well as Head of the VDI Advisory Board "Reliability Management". Since 2003 he has been member of the DIN/DKE Standardization Committee K132 "Reliability". He was elected to be a member of the review board of the German Research Foundation in 2012. 2013 he was elected to be the managing director of the WiGeP e.V. As of 2015 he has been a member of the National Academy of Science and Engineering.