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A Health Index Framework for Condition Monitoring and Health Prediction

Alexander Athanasios Kamtsiuris[1], Florian Raddatz[2], Gerko Wende[3]

[1,2,3] *German Aerospace Center (DLR) Institute of Maintenance, Repair and Overhaul, Hamburg, 21129, Germany*
alexander.kamtsiuris@dlr.de
florian.raddatz@dlr.de
gerko.wende@dlr.de

ABSTRACT

In the field of Maintenance, Repair and Overhaul (MRO), stakeholders such as operators or service providers have to keep track of the health status of fleets of complex systems. The ability to estimate the future health status of these systems and their components becomes more pivotal when seeking to efficiently operate and maintain these systems. Today, these stakeholders have access to a lot of different data sources regarding fleet, operation schedule, ambient condition, system and component information. Many different prognostic methods from different disciplines are available and will further improve henceforward. In many cases these data sources and methods function as isolated methods in their own field. This fragmentation makes a holistic prognosis very challenging in many cases. Therefore, stakeholders need information integrating methods and tools to gain an exhaustive insight into the health status development of the complex assets they are operating or maintaining, in order to make well-founded decisions regarding operation or maintenance planning. In this paper, a Python-based health index framework is presented. It enables users to integrate operation schedules of different detail levels with enriching data sources such as ambient condition data. Furthermore, it provides methods to design complex asset systems which are linked via their construction, function or degradation mechanisms/health indices via transfer relations. It allows to monitor the asset's condition based on operation data and to simulate different operation scenarios regarding the health index development.

1. INTRODUCTION

System Health Management (SHM) plays a key role in today's Maintenance, Repair and Overhaul (MRO) activities by making the asset's operation economically more efficient and economically competitive. Many Health Management approaches need the development of the health status development according to individual mission profiles of the asset as input for their simulation. Examples are the estimation of operating costs as in (Pohya, Wehrspohn, Meissner, & Wicke, 2021) or deriving prescriptive maintenance strategies as in (Meissner, Rahn, & Wicke, 2021).

A key functionality of Digital Twins of systems is the ability to simulate future health development (Meyer et al., 2020). Many different methods to predict the Remaining Useful Life (RUL) of components have been developed so far (van Nguyen et al., 2019). In practice, for system designers and operators, the system-level prognostics to predict the System Remaining Useful Life (SRUL) are needed since the degradation of the different system components influence each other and hold an additional potential for uncertainty (Tamssaouet, Nguyen, Medjaher, & Orchard, 2021). Often, the operating condition or environmental conditions are factored into the RUL prediction as sources of uncertainty. Moreover, the RUL prediction is carried out based on the individual history of the concerning component or system. In order to allow more precise health prediction and to improve the versatility of decision makers, considering the impact of specific future operating settings and environmental conditions in RUL predictions has gained interest. (Chang, Lin, & Zio, 2022)

In this paper, a generic framework to integrate functional and hardware related information with diagnostic and prognostic methods is proposed. It allows to estimate the current as well as to predict the future health state on a system level, expressed by health indexes, based on operating and environmental conditions. It provides a method to analyze the interdependence of different degradation mechanisms on the system health state and the SRUL. The results can be used for health management activities. The framework is developed in Python and accessible via `https://github.com/DLR-MO/system-health-index-framework`.

The main aspects of the framework are described in section 2. Using the new Commercial Modular Aero-Propulsion Sys-

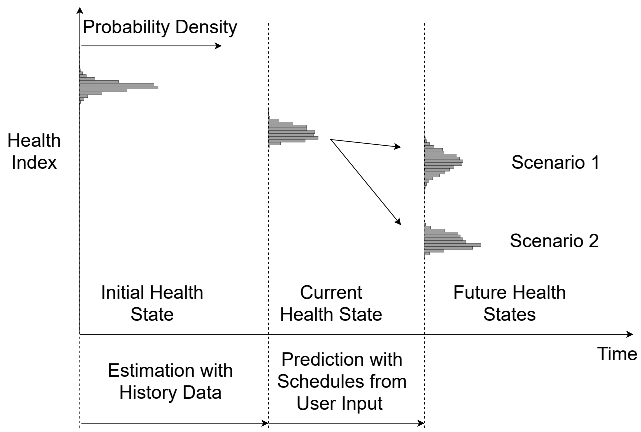

Figure 1. Current and Future Health State

tem Simulation (N-CMAPSS) data presented in (Arias Chao, Kulkarni, Goebel, & Fink, 2021), key functionalities of the framework are demonstrated in section 3. Further development of the framework is discussed in the section 4.

2. Aspects of the System Health Index Framework

The proposed framework allows to integrate health state estimation and health prediction methods in order to monitor health condition and to simulate the future health status of an arbitrary complex system based on user-defined schedules of ambient and operating conditions, as shown in Figure 1. The health state of a component or system is expressed with the health index. Starting with the current health state the framework allows to simulate different scenarios regarding future operating schedules. In the following subsections different aspects of the framework will be discussed in further detail.

2.1. System Health Index

A system is a hierarchically organized group of subsystems, components or parts which are constructively and functionally related (Kossiakoff, Biemer, Seymour, & Flanigan, 2020). Accordingly, also the different health states interfere with each other. The health state of each of the above mentioned objects can be described by a health index. The health index incorporates multiple, sometimes hidden and not observable degradation processes of different components and therefore allows an analysis of the current and future health states of systems (Sun, Zuo, Wang, & Pecht, 2012).

In this work the definition for the health index proposed in (Arias Chao et al., 2021) is used. The health index hi is defined as in Equation (1). Parameter values of a measurable real or virtual sensor are used and normalized with known reference values for the respective parameter, e.g. known temperature thresholds compared to the temperature values when there is no wear $w = 0$. The health index reaches $hi = 0$ if

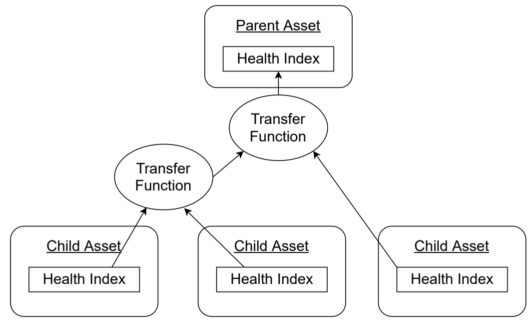

Figure 2. Parent-Child Concept for System Description

the wear w equals the defined threshold wear $w_{threshold}$. The wear depends on time and can also be influenced by operating conditions.

From real and virtual sensor readings and by using health state estimation methods, the history or current health state of a system and its components is estimated. These estimations provide the foundation for the future health state prediction.

$$hi(t) = 1 - \frac{w(t)}{w_{threshold}} \quad (1)$$

Each component has at least one health index for the description of its general health state. The overall health index (HI) of a component can be derived from the set of assigned subordinate health indexes (hi), which is shown in Equation 2. Transfer functions $f_{Transfer}$ express how a certain set of health indexes influences another health index.

$$HI = f_{Transfer}(hi_i) \ \ (i = 1, ..., n) \quad (2)$$

For components in series, usually the minimum health index hi governs the resulting HI. However, for components in parallel, where the failure of one component does not cause a failure of the parent system, the HI corresponds to the maximum hi (Rodrigues et al., 2015). Other transfer functions e.g. functions which apply weights to health indexes, are possible and can be integrated into the presented framework. This is necessary e.g. to describe the health status of an aircraft engine's turbine rotor assembly with cracks on different turbine blades and in different crack propagation states.

This framework uses the parent-child-logic to describe and model systems, as shown in Figure 2.

2.2. Current Health State Estimation and Health State Prediction

In order to predict future health states, it is important to estimate the current health state of a system and its components. The current health state is estimated by using actual and virtual sensor signals. Sensor noise and different operational and environmental conditions have an impact on the sensor

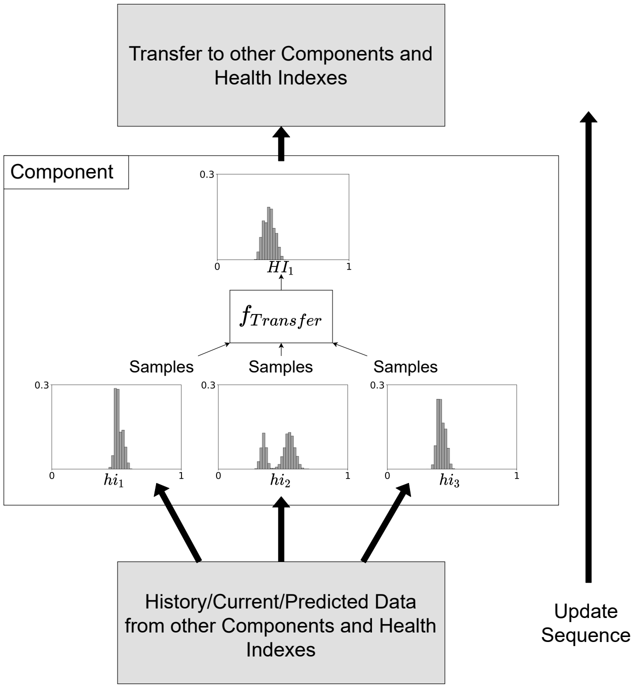

Figure 3. Update Process

measurements, therefore filtering and normalization methods need to be applied in order to get comparable reference values for the sensor parameters independently from the above mentioned factors (Hajiha, Liu, & Hong, 2021). Different promising methods to baseline the sensor data have been developed recently, such as in (Baptista, P. Henriques, & Goebel, 2021) by using neural networks or in (Hou et al., 2021) by introducing sparsity indexes for rotating machines.
Based on the estimated current health state, future health states can be predicted. Among other techniques, health index-based approaches for system health analysis have been found to be effective methods. Various prognostic algorithms such as neural or Bayesian networks have been used. The output can be either the RUL or the offset from normal, healthy states. (Kim, Choi, & Kim, 2021)
This framework uses current and history (virtual) sensor readings and prior health state estimates to calculate the probability distribution for the current health state. Expressing the health state with a probability distribution considers the inherent uncertainty of that estimate. The role of uncertainty is further described in section 2.3.

The health state prediction methods estimate the decrease of the health indices in correlation with an arbitrary set of operational and environmental parameters. The framework allows to integrate prognostic algorithms from different sources. The inputs are the current health state distribution, the prior health state development as well as the user-defined input parameters from the simulation schedules, which are described in more detail in section 2.4. The outputs are increments of health index consumption per simulation step.

2.3. Uncertainty in Condition Monitoring and Prognostics

Evaluating the uncertainty of estimations plays an important role in condition monitoring and prognostics. (Sankararaman & Goebel, 2015) define four sources of uncertainty in condition-based monitoring and prognostics. Uncertainty management addresses the influence on minimizing uncertainty sources and to administer risk-decreasing measures, such as less present uncertainty by less uncertain inputs from sensors. Uncertainty quantification needs a sensitivity analysis step in order to identify the input parameters which impact the output of a model the most (Razavi et al., 2021).
Present uncertainty describes the uncertainty in estimating the current health state of a system and it is depending on the quality of the sensors and the filtering methods applied. **Future uncertainty** results from the lack of knowledge about future loading, operating, environmental and usage conditions. **Modeling uncertainty** refers to the uncertainties regarding the prediction model, such as the model's output response on the given inputs of loading, operating, environmental and usage conditions or the model parameters. **Prediction method uncertainty** describes the uncertainty from combining the prior three sources of uncertainty and their impact on the prediction. The Monte Carlo sampling is used most commonly as uncertainty propagation method. Random samples are drawn (such as initial health state, operating conditions, etc.) and the corresponding realizations are computed (e.g. health state after a certain time period). Monte Carlo can be computationally expensive, however, compared to faster uncertainty propagation techniques, it allows to reduce the uncertainty of the estimated probability distribution, the prediction method uncertainty (Sankararaman & Goebel, 2015). This framework uses Monte Carlo sampling for uncertainty propagation, which is incorporated into the update process in Figure 3.

2.4. Discrete Event Schedule

In the context of this framework, schedules are lists of events of arbitrary granularity such as flight, take-off, turn, etc. They consist of historic data and future data. Uncertainty of events, as described in subsection 2.3, have an significant impact on the prediction results. The schedules contain an arbitrary number of parameters used for health state estimation and health state prediction methods. Different techniques to enhance the schedules can be integrated when using the framework.

2.5. Process

1. <u>**Model**</u>

   (a) **Creating the System**

- Objects of the *Component* class are initialized and linked using the Parent-Child-principle
- Per component a general health index (HI) is initialized
- Standard transfer relations between components are initialized

(b) **Defining and Adding Health Indexes to the Model**

- Objects of the *Health_Index* class are defined and added to the model's components
- Per health index (hi) start values, reference values, health state estimation method and prediction method are defined
- The transfer target HI for the later update process is automatically derived from the component's transfer relations or can be customized by adding an object of the class *Transfer* to the model. This allows to link health indexes with arbitrarily complex transfer functions.

(c) **Adding History Data to the Model**

- A data frame using the principle for discrete event schedules described in subsection 2.4 is created and added to the component's *history* attribute.
- Running the *Component* class' *estimate_current_health_state* function updates the health index values of the model bottom up for every time step in the history data. The scheme for the update process is shown in Figure 3.

2. **<u>Simulation</u>**

(a) **Creating Simulation Schedules**

- The model is loaded and the history data is fetched.
- Using the system's history data, simulation schedules are generated with the information from the user input.

(b) **Running the Simulation**

- The algorithm loops through each simulation schedule and each time step, continuously predicting a degradation increment and updating the system's health state with the update process.
- after the simulation run, each health index progress dependant on the simulation schedules can be analyzed.

3. CASE STUDY

In order to demonstrate the functionalities and the process of the framework described in section 2.5 a system consisting of multiple components and various degradation mechanisms respectively health indexes is generated. Afterwards, a set of simulation schedules is created and the simulation is run.

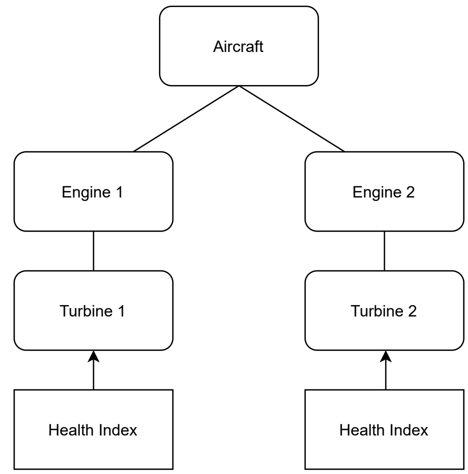

Figure 4. System Example

In a first step, an aircraft model which consists of two engines and respectively two High Pressure Turbine (HPT) modules is set up. For each HPT module, the health index based on the measured total temperature at the HPT outlet is established. Therefore, this health index incorporates not only the wear of the component, which it is directly linked to, but the wear of all components which have an impact on the reference sensor measurement. As transfer functions for the health indexes $min()$ is chosen, since due to to safety obligations, the unhealthiest turbine dictates the overall system's health status. The model is depicted in Figure 4.

For the introduced health indexes, health estimation and prediction methods need to be defined.
For demonstration purposes, data from (Arias Chao et al., 2021), which is created with the Commercial Modular Aero-Propulsion System Simulation (CMAPSS) model, described in (Frederick, DeCastro, & Litt, 2007), is used. The data set N-CMAPSS contains engine run-to-failure data for a fleet of aircraft engine units under real flight conditions. A method for the current health state estimation and the future health prediction is derived by using the data set $DS01$. Generally, the system's degradation in (Arias Chao et al., 2021) is induced by modifying the engine health parameters flow and efficiency of different engine modules. In practice, these parameters are not measured, however, the degradation is indicated by observable sensor measurements such as temperature measurements in the turbine.
In this case study, the method used in (Arias Chao et al., 2021) for engine health parameter alteration is transferred to the health index decrease in order to model its degradation over time. The initial wear δ_0 is obtained from a uniform distribution. The first phase of a normal, linear degradation until time t_s is modeled with a constant slope a_n and with t being the flight cycles.

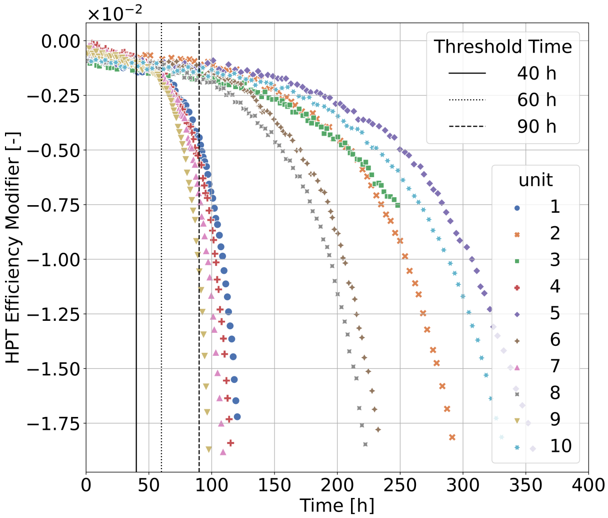

Figure 5. Development of High Pressure Turbine Efficiency Modifier Over Time from the N-CMAPSS Data Set DS01

$$\delta_n(t) = a_n t + \delta_0 \;\; \forall \, t < t_s \tag{3}$$

t_s is the time when the excitation energy exceeds the maximum excitation energy E_{max} of a component for the first time.

$$t_s = inf\{t \geq 0 \mid E(t) > E_{max}\} \tag{4}$$

The excitation energy is the integral of the power consumed and produced by a component over a certain time interval. In case of Equation 5, t denotes the time in hours.

$$E(t) = \int_0^t P(t)\, dt \tag{5}$$

Between equal subsystems, the maximum excitation energy E_{max} varies due to the individual material properties. Once t_s is reached, the abnormal degradation δ_a is described by the following model:

$$\delta_a = 1 - e^{a(t-t_s)^b} + \delta_n(t_s) + \xi \tag{6}$$

a and b are uniformly distributed parameters for the exponential function, t is the number of cycles and ξ is the process noise, which covers the uncertainty e.g. originating from sources such as maintenance events, and therefore can be either positive or negative.
The degradation in the data set $DS01$ is governed by a decrease of the HPT efficiency.

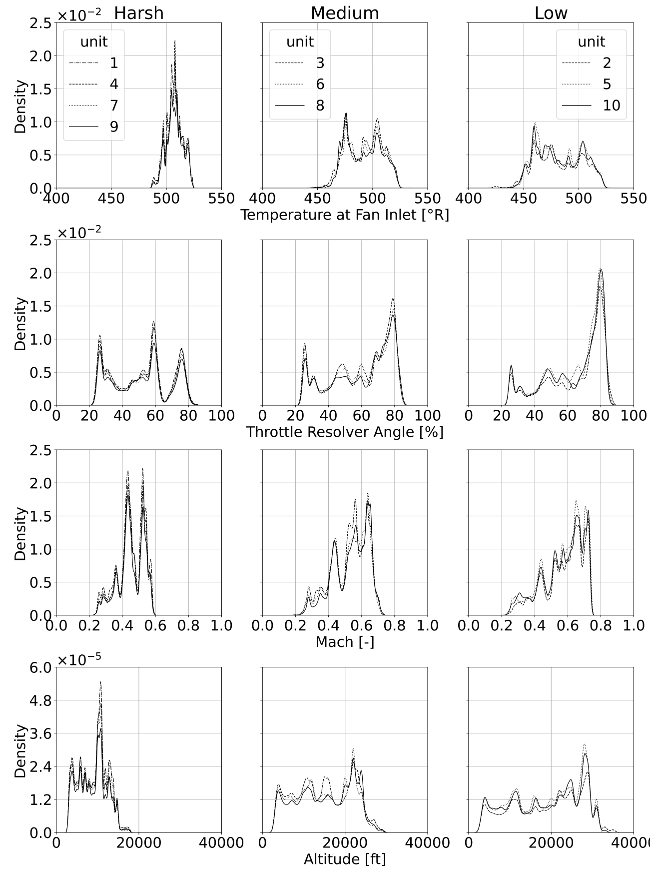

Figure 6. Operation Settings from N-CMAPSS data set $DS01$

Figure 5 shows the decrease of the HPT efficiency modifier over the flight hours collected by each unit. As input variables for the flights, the operation settings depicted in Figure 6 are used by the original authors. The throttle resolver angle (TRA) describes the used relative power setting for the engine. The onset of abnormal degradation marks the hours collected when E_{max} is reached. Roughly, there are three characteristic groups of flight trajectories regarding the t_s, where both similar onset of abnormal degradation and similarity in operating settings can be observed, see Table 1 and Figure 6. The groups are called $Harsh$, $Medium$ and Low in this work, related to each group's characteristic onset of abnormal degradation and the respective excitation power P_{rel}. Unit 3 differs from that behaviour, since the operating settings resemble the $Medium$ class flights, whereas the trajectory is closer to the Low class. A possible explanation might be the method, how variable material properties are incorporated in the synthesis of the data in the original work of (Arias Chao et al., 2021). The individual maximum excitation energy of a component is modelled by a Gaussian distribution. With a higher maximum excitation energy, the shift from linear to abnormal degradation is experienced later, even with relatively harsher operating conditions.

Table 1. Flight Intensity Classes for Schedule Generation

Intensity Class	Units	$t_{threshold}$ [h]	P_{rel} [1/h]
Harsh	1,4,7,9	40	-0.025
Medium	3,6,8	60	-0.017
Low	2,5,10	90	-0.011

Table 2. Simulation Parameters

	Harsh	Low
$cycle\ length \quad [h]$	$\mathcal{N}(1.2, 0.2)$	$\mathcal{N}(4, 0.75)$
$P_{rel} \quad [1/h]$	-0.025	-0.011
a	$\mathcal{U}(0.001, 0.003)$	$\mathcal{U}(0.001, 0.003)$
b	$\mathcal{U}(1.4, 1.6)$	$\mathcal{U}(1.4, 1.6)$
ξ	$\mathcal{N}(0, 0.001)$	$\mathcal{N}(0, 0.001)$
$n_{SimulationRuns}$	100	100
$n_{HistoryCycles}$	20	20
a_n	-0.001	-0.001
δ_0	$\mathcal{U}(0.9, 1.)$	$\mathcal{U}(0.9, 1.)$
Transfer Function	$min()$	$min()$

Harsh conditions have relatively higher temperatures at the fan inlet compared to low intensity operation conditions. The inlet temperature seems to have a higher impact on increasing the excitation energy level than the averagely higher TRA observed in the Low group.
The relative excitation power is calculated with Equation 7.

$$P_{rel} = \frac{1}{t_{threshold}} \tag{7}$$

For demonstration purpose, the equations 3 - 7 are used for both the health state estimation as well as for the health state prediction in this case study.

Event schedules described in subsection 2.4 are generated and the health state development for different operating and environmental conditions is simulated. The current health state is estimated starting from the beginning of life of the system until the time point $t_{current} = 20 \quad cycles$ using $harsh$ condition setting, which implies a excitation power of $P_{rel} = -0.025 \quad [1/h]$. For each of the two operation intensity classes $harsh$ and low, a simulation with $n_{SimulationRuns} = 100$ schedules is set up. The two scenarios have different excitation power parameters P_{rel} and different $cyclelength$ parameters, an overview of the used parameters is given in Table 2.

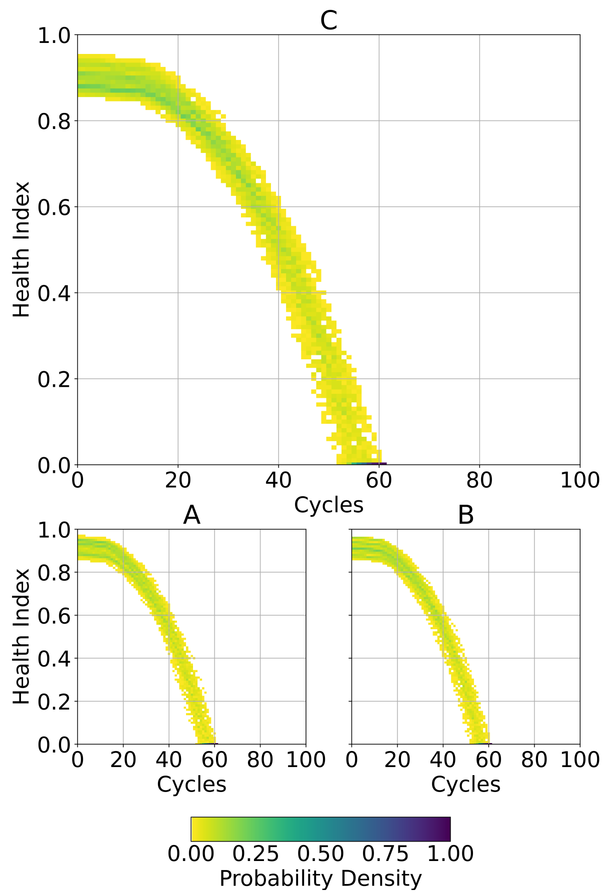

Figure 7. Prediction for Harsh Intensity Operating Conditions. A: hi EGT Turbine 1, B: hi EGT Turbine 2, C: HI Aircraft

The prediction for the simulation of future harsh operating conditions is depicted in Figure 7. Around 15 cycles into the simulation the abnormal degradation is reached. SRUL for the Aircraft with probability $p = 1$ is at 61 cycles.
The distributions of the turbine health indexes in Figure 7 A and B show an increasing spread of possible health indexes at each time step. Towards the end the spread then decreases due to the probability p of $hi = 0$ reaching $p = 1$. The applied transfer function $min()$ causes a shift to the lower health indexes for the aircraft level health index in Figure 7 C.

The prediction for the simulation of future low intensity operating conditions is depicted in Figure 8. Even though the intensity is lower than in scenario 1, SRUL with probability $p = 1$ is reached already at 55 cycles. This is due to the higher $cycle\ length$ in scenario 2, which leads to an earlier excess of the excitation energy level E_{max} and therefore an

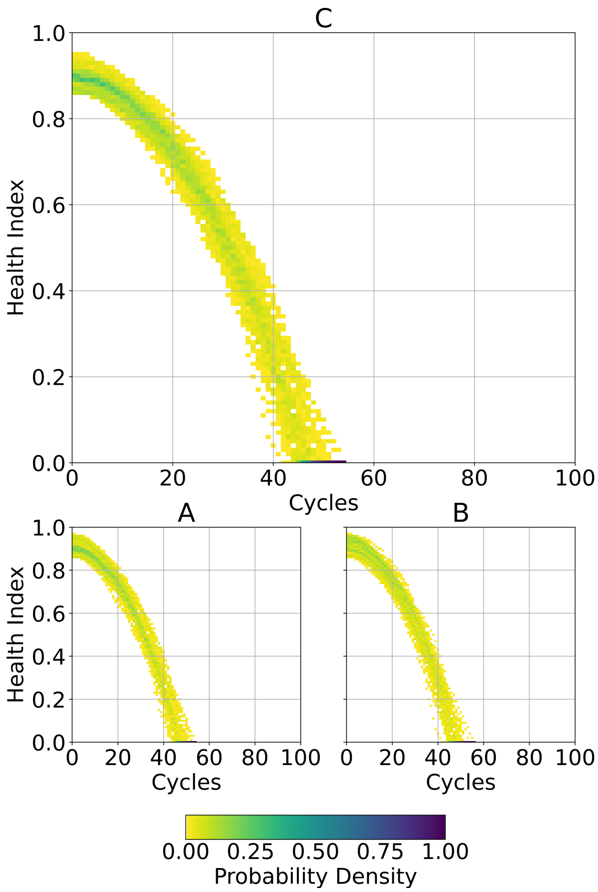

Figure 8. Prediction for Low Intensity Operating Conditions. A: hi EGT Turbine 1, B: hi EGT Turbine 2, C: HI Aircraft

earlier onset of abnormal degradation. Turbine 1 with averagely lower health indexes dictates the overall system health index of the aircraft, especially in the first cycles.

In both scenarios, with progressing time, the spread of the health index increases until the first simulations reach $hi = 0$. The possibility of using different transfer functions shows, that more sophisticated dependency between health index degradation trajectories can be established, which allows more accurate decision making for the user.

4. Conclusion

The proposed framework establishes a method to integrate health state estimation and health state prediction for complex systems. It allows to create system models using the parent-child principle and to add health indexes for different degradation mechanisms. These health indexes can be linked via transfer functions. The framework combines history data with future event schedules to simulate future health states. It takes into account the uncertainty propagation by using Monte-Carlo-Sampling. The framework's output is an important input for further health management activities.

In the future, the integration of online and offline prognostic metrics in order to assess the impact of the diagnosis and prognostic algorithms on the uncertainty will be investigated. Furthermore, uncertainty management functionalities such as sensitivity analysis in order to analyse the impact of single factors on the prediction uncertainty will be assessed, e.g. for sensor improvement activities.

Moreover the establishment of interdependence between health index developments of different hierarchical levels will be improved. Also, other uncertainty propagation techniques to improve the performance of the simulation will be investigated.

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