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Major Challenges in Prognostics: Study on Benchmarking Prognostics Datasets

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ABSTRACT

Even though prognostics has been defined to be one of the most difficult tasks in Condition Based Maintenance (CBM), many studies have reported promising results in recent years. The nature of the prognostics problem is different from diagnostics with its own challenges. There exist two major approaches to prognostics: data-driven and physics-based models. This paper aims to present the major challenges in both of these approaches by examining a number of published datasets for their suitability for analysis. Data-driven methods require sufficient samples that were run until failure whereas physics-based methods need physics of failure progression.

1. INTRODUCTION

Condition based maintenance (CBM) is a preventive maintenance strategy, in which maintenance tasks are performed when need arises. The need is determined by tracking the health status of the system or component (Camci and Chinnam, 2010: Eker et al., 2011). CBM is a proactive process involving two major task: diagnostics and prognostics. Diagnostics is the process of identification of a failure, whereas prognostics is the process of forecasting the time to failure. Time left before observing a failure is described as remaining useful life (RUL) also called remaining service or residual life (Jardine et al., 2006).

An example of degradation in health level of an asset is shown in Figure 1. The P-F interval is the time interval between potential failure which is identified by health indicators, and an eventual functional failure. With CBM it's necessary that the P-F interval is long enough to enable corrective maintenance action to be taken (Jennions, 2011).

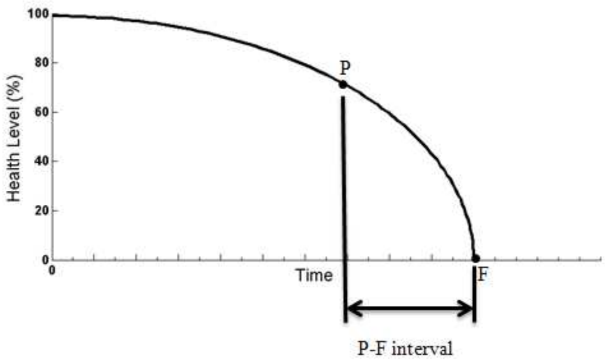

Figure 1. P-F curve of an asset

Diagnostics is a more mature field than prognostics. Once degradation is detected, unscheduled maintenance should be performed to prevent the failure consequences. It is not uncommon to spend more time in maintenance preparation than in performing the actual maintenance due to lack of resources. In prognostics on the other hand, maintenance preparation could be performed when the system is up and running, since the time to failure is known early enough. Thus, the actual maintenance duration becomes the major contributor of the downtime. Figure 2 illustrates the comparison of diagnostics and prognostics.

Performing maintenance preparation when the system is up and running has a great effect on reducing the operation and support costs. In addition to the reduced down time, the inventory cost will be reduced since more time will be available for obtaining required parts. The efficiency in logistics & supply chain will be increased due to the better preparation for maintenance. The life cycle cost of the equipment will be reduced, since they are used until end of their lives.

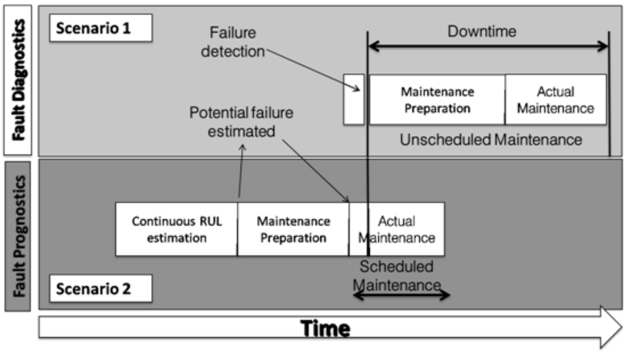

Figure 2. Comparison of failure diagnostics and prognostics maintenance scenarios

Despite the potential value in prognostics, it is considered to be one of the most challenging tasks in CBM (Zhang et al., 2006: Peng et al., 2010). Prognostics involves two phases as shown in Figure 3. The first phase of prognostics aims to assess the current health status. Severity detection, health assessment, or degradation detection are the terms used for describing this phase in the literature. This phase could also be considered under diagnostics. Pattern recognition techniques such as classification or clustering can be utilized in this phase. The second phase aims to predict the failure time by forecasting the degradation trend and by identifying remaining useful life (RUL). Time series analysis, trending, projection or tracking techniques are used for this phase.

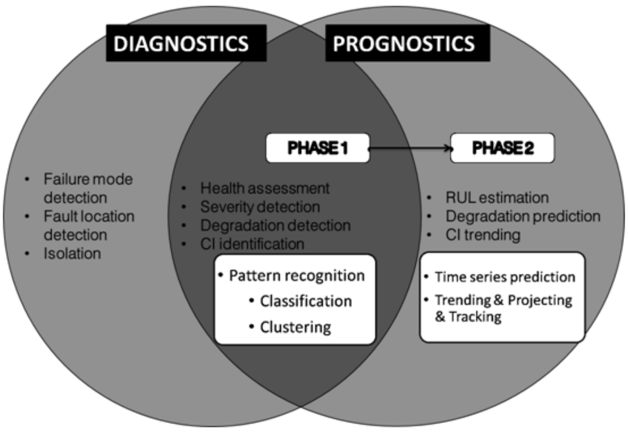

Figure 3. Phases of prognostics and diagnostics

Many academic papers with prognostics titles only consider the first phase (Qiu et al., 2003; Ocak et al., 2007). However, prognostics without the second phase will not be complete and will not lead to RUL estimation. This paper focuses on the second phase of prognostics.

Prognostics methods can be analyzed in two major categories: Data-driven and physics-based models. Data-driven models utilize past condition monitoring data, current health status of the system, and degradation of similar systems. Physics-based models employ system specific mechanistic knowledge, defect growth formulas, and condition monitoring data to predict the RUL of systems (Heng et al., 2009).

This paper aims to discuss the challenges for data-driven and physics-based prognostics and presents several case studies. Section 2 reports the requirement analysis and challenges of data-driven and physics-based prognostics models. Section 3 discusses several prognostic case studies. Finally section 4 concludes the paper with an emphasis on future research tasks.

2. CHALLENGES IN PROGNOSTICS MODELING

Both data-driven and physics-based models have different requirements to model the degradation and predict the RUL of a system. Challenges and requirements of both approaches are given in distinct sub-sections below.

2.1. Data-Driven Models

Data driven models intend to model system behavior using regularly collected condition monitoring data instead of using comprehensive system physics or human expertise (Heng et al., 2009). Data-driven approaches are classified into two categories in general. These are statistical and machine learning approaches. Statistical approaches construct models by fitting a probabilistic model to the available data. Machine learning approaches attempt to recognize complex patterns and make intelligent decisions based on empirical data.

Both statistical and machine learning methods use the degradation patterns of sufficient samples representing equipment failure progression. This requirement is the major challenge in data-driven prognostics since it is often not possible to obtain samples of failure progressions. Industrial systems are not allowed to run until failure due to its consequences especially for critical systems and failure modes. However quality and quantity (sample size) of system monitoring data has a high influence on data-driven methods. Sample sizes of prognostic datasets in the literature range from 10 to 40 (Camci and Chinnam, 2010; Baruah and Chinnam, 2005; Huang et al., 2007; Gebraeel et al., 2005; Eker et al., 2011). In this paper datasets will be compared to sample sizes provided in the references above as quantitative analysis.

Most of the electro-mechanical failures occur slowly and follows a degradation path (Gebraeel et al., 2009). Failure degradation of such a system might take months or even years. This challenge has been addressed in the literature in the following ways:

1. Accelerated aging: Equipment is run in a lab environment with extreme loads and/or increased speed to allow faster

failure. Structural health monitoring applications are a good example of this type of failure progression. Test specimens are subjected to cyclic loading experiments so that cracks are propagated faster than normal degradation process (Camci et al., 2012: Diamanti & Soutis, 2010: Papazian et al., 2009). Camci and Chinnam, (2010) used imitations of real components which are made by vulnerable materials so that failure progresses faster than normal.

2. Unnatural failure progression: A predefined degradation formula is used to define the discrete failure states and duration to be spent in each state. Failure progression in a railway turnout has been modeled using exponential degradation (Eker O. F., 2011).

Each solution has its own strengths and weaknesses with some level of failure degradation representation capability.

2.2. Physics-Based Models

Physics-based models employ a physical understanding of the system in order to estimate the remaining useful life of an asset. Even though samples of failure degradation are not essential in physics based prognostics, the physical rules within the system should be known in detail. The first phase in physics based prognostics is to employ residuals that represent the dispersion of sensed measurements from their expected values of healthy systems (Namburu et al., 2003). The second phase in physics based prognostics requires mathematical modeling of failure degradation.

There exist two major challenges in physics based prognostics: 1) the lack of sufficient knowledge on physics of failure degradation and 2) the inability to obtain the values of the parameters in the formulations. Thus, sufficient component/system information and good understanding of failure mechanisms are essential and skilled personnel is also required in physics based models (Zhang et al., 2009). Environmental and operating conditions might be used as inputs and constitute added dimension to be considered.

3. BENCHMARKING DATASETS

Several publicly available datasets are analyzed in this section for their suitability in testing prognostic approaches. As mentioned in section 2, a prognostic dataset is expected to have a minimum sample size around 10 in order to perform data-driven modeling effectively. Regarding physics-based prognostics side, datasets will be examined with regards to: 1) If a mathematical degradation model exists for the specific application and 2) whether parameters in the model are provided with datasets or not. The applicability of data driven and physics based prognostics methods have been studied and results are presented in following subsections.

3.1. NASA Data Repository (5 dataset)

NASA Ames prognostics data repository (2012) is a growing source covering several sets of prognostic data contributed by universities, companies, or agencies. Datasets in the repository consist of run-to-failure time series data representing the case study under examination. There are seven sets of prognostics dataset available. In this section analysis of five datasets for data-driven or physics-based modeling is presented.

3.1.1. Milling Dataset

Sixteen milling inserts were degraded by running them at different operating conditions (Agogino and Goebel, 2007). Once the flank wear on the milling insert exceeded a standard threshold level the tool was considered to have failed. Flank wear was observed by a microscope on the flank face of the cutting tool caused by the abrasion of hard constituents of workpiece material which is commonly observed during the machining of steels or cast irons. Measurements of acoustic emission, vibration and current were collected as indirect health indicators. There are eight different operating conditions leading to only two samples for each operating condition.

Effective data-driven modeling is very difficult, if not impossible, using only two samples of failure degradation. Several tool life or tool-wear rate models, mostly based on Taylor's formula (Yen et al., 2004), have been selected for physics based prognostics and are displayed in Table 1.

Tool Life Models	Tool Wear Rate Models
$VL^n = C$ (1)	$dW/dt = \frac{C}{H}\frac{F_f}{Vf}V_s + Bexp^{\frac{-E}{RT_f}}$ (5)
$V^x f^y d^z L = C$ (2)	
$V = \frac{C}{L^p f^q d^r (BHN/200)^t}$ (3)	
$TL^n = C$ (4)	
$C, x, y, z, n, p, q, r, t = Constants$	
$V = Cutting\ speed$	
$L = Tool\ life$	
$f = Feed\ rate$	
$d = Depth\ of\ cut$	
BHN ($Brinell\ Hardness\ Number$) $= Workpiece\ hardness$	
$H = Cutting\ tool\ hardness$	
$T = Cutting\ temperature$	
$T_f = Cutting\ temperature\ in\ tool\ flank$	
$E = Process\ activation\ energy$	
$R = Universal\ gas\ constant$	
$F_f = Normal\ cutting\ force$	
$V_s = Sliding\ speed$	

Table 1. Tool life and wear models

In physics-based prognostics side, Taylor tool life (Eq. 1) and its extended versions in Eqs. 2-3, are well known life models employed in machining applications. Each of them can be applied into tool degradation scenarios separately. Tool life is the duration in which a tool can be operated properly before it starts to fail. In machining applications a predetermined flank wear upper level is used as a failure criterion. Tool life and rate of wear are sensitive to changes in cutting conditions. The relationship between tool life and machining parameters (e.g. cutting speed, feed, and depth of cut) are described by these equations. Cutting speed is considered as the difference in speed between the cutting tool and the workpiece. Feed rate is the velocity of a tool moving laterally across the workpiece which is perpendicular to the cutting speed. The depth of cut is how deep a workpiece is penetrated. Takeyama and Murata's tool wear rate model, shown in Eq. 5, describes the relationship between rate of volume loss on the tool insert, cutting distance and diffusive wear per cycle. Even though parameters specific to tool material or workpiece (e.g. cutting tool hardness) can be found in machining tool handbooks, operating or environmental condition parameters such as cutting temperature and sliding speed are not provided with the dataset.

For the above reasons this dataset is found to be not suitable for data-driven and physics-based prognostic models.

3.1.2. Bearing Dataset

Three sets (each set consist of four bearings) of tapered rolling element bearings have been run to failure at the same operating conditions (Lee et al., 2007). Accumulated mass of debris was collected for each experiment, the amount of debris being considered a direct health indicator of the bearing health (Dempsey et al. 2006). In contrast to the milling dataset, the direct health indicator (amount of debris collected) was not provided with the dataset. Vibration data was collected regularly as an indirect health indicator. After exceeding 100 million revolutions the bearings were failed due to a crack or outer race failure (Qiu et al., 2006).

Yu-Harris (Y-H) and Kotzalas-Harris (K-H) models were selected to be used in a physics-based prognostic approach. Both bearing spall initiation and spall progression models found in (Orsagh et al., 2003: Yu, and Harris, 2001) are shown in Table 2. Yu and Harris' bearing stress-based spall initiation formula is a function of dynamic capacity (Q_c) and the applied load (Q) as shown in Eq. 6. Dynamic capacity is also a function of bearing geometry and stress. Once initiated, a spall grows very quickly and a bearing has only 3% to 20% of its remaining useful life left (Kotzala and Harris, 2001). The Kotzala-Harris spall progression rate model is a function of spall progression region width (W_{sp}), and is described with regards to maximum stress($\sigma_{\max}$), average shearing stress(τ_{avg}), and spall length(S_p).

Similar to the previous dataset some parameters to be used in physics based modeling are not found in the dataset (e.g.$\sigma_{max}, \tau_{avg}, \tau_{avg}$).

Challenges emerge in this dataset are:

- Three run-to-failure sets of samples are considered insufficient for data-driven modeling when compared to dataset sample sizes found in literature.
- Lack of parameters to be used in physics-based modeling.

Spall initiation model

$$\boldsymbol{L_{10} = \left(\frac{Q_c}{Q}\right)^{\frac{x+y+z}{3}}} \quad (6)$$

where:

$$\boldsymbol{Q_c = A_1 \Phi D^{\frac{2z-x-y-3}{z+x+y}}} \quad (7)$$

$$\boldsymbol{\Phi = \left[\left(\frac{T}{T_1}\right)^z \frac{u(D\Sigma\rho)^{\frac{2z-x-y}{3}}}{(a^*)^{z-x}(b^*)^{z-y}} \frac{d}{D}\right]^{\frac{-3}{z+x+y}}} \quad (8)$$

Spall progression model

$$\boldsymbol{\frac{dS_p}{dN} = C(W_{sp})^m} \quad (9)$$

where:

$$\boldsymbol{W_{sp} = (\sigma_{max} + \tau_{avg})\sqrt{\pi S_p}} \quad (10)$$

$\boldsymbol{A_1 = Material\ property}$
$\boldsymbol{T = a\ function\ of\ the\ contact\ surface\ dimensions}$
$\boldsymbol{T_1 = value\ of\ T\ when\ a/b = 1}$
$\boldsymbol{u = number\ of\ stress\ cycles\ per\ revolution}$
$\boldsymbol{D = ball\ diameter}$
$\boldsymbol{\rho = curvature}$
$\boldsymbol{d = component\ diameter}$
$\boldsymbol{a^*, b^* = function\ of\ contact\ ellipse\ dimensions}$
$\boldsymbol{S_p = spall\ length}$
$\boldsymbol{W_{sp} = spall\ progression\ region\ width}$
$\boldsymbol{C\ and\ m = constants}$
$\boldsymbol{\sigma_{max} = maximum\ stress}$
$\boldsymbol{\tau_{avg} = average\ shearing\ stress}$

Table 2. Bearing fatigue life models

3.1.3. Li-ion Battery Dataset

Electric unmanned aerial vehicle (eUAV) li-ion batteries were used in this prognostic approach (Saha and Goebel, 2007). The batteries were charged and discharged at different ambient temperatures and different load currents. There are 4 samples under the same operating conditions and in total 36 samples are provided. Battery capacity fade is chosen as a failure indicator for these experiments. It was assumed that 30% of battery capacity fade, for example a reduction of 2000 to 1400 mAH was considered as failure. Voltage, current and battery temperature measurements are provided with the dataset as indirect health indicators. Impedance and capacity measurements were given with the dataset as damage criteria which are direct health indicators.

Only four set of batteries under the same operating and environmental conditions are not enough to apply data-driven prognostics in an effective way.

Typically battery capacity or end of life (EOL) modeling is done for physics-based prognostics purposes. A remaining battery capacity model can be found in the literature (Rong and Pedram, 2006). All parameters, other than constant coefficients which are determined from experimental testing by curve fitting, are available to be employed in their model. This dataset was therefore found to be eligible for physics-based modeling.

3.1.4. Turbofan Engine Degradation Simulation Dataset

This dataset contains 4 sets of data each of which is a combination of 2 failure modes and 2 operating conditions. Each set has at least 200 engine degradation simulations carried out using C-MAPSS which are divided into training and test subsets (Saxena and Goebel, 2008). Twenty one different sensor measurements as well as RUL values for test subsets are given (Saxena et al., 2008). However, health indicators were not provided with the dataset.

Degradation in the HPC and Fan of the turbofan engine is simulated and dataset consists of multiple multivariate time series data. The simulations employ several operating conditions. The model that the dataset owners applied is exponential degradation shown in Eq. 11 where (d) is initial degradation, (A) is a scaling factor, $(B(t))$ time varying exponent, and $(\mathrm{t}h_w)$ is upper wear threshold. The model is a generalized equation of common damage propagation models (e.g. Arrhenius, Coffin-Manson, and Eyring models).

$$h(\mathrm{t}) = 1 - d - \mathrm{A}exp^{B(t)}/\mathrm{t}h_w \qquad (11)$$

The dataset is eligible for data-driven approach since sufficient data and RUL values are available with dataset. Either statistical or machine learning data-driven models can be employed to predict the RUL of turbofan engines. On the other hand, it is not appropriate for physics based modeling since the health index parameters are not given and no physics-based model found for whole engine system degradation.

3.1.5. IGBT Accelerated Aging Dataset

The dataset involves thermal overstress aging experiments of Insulated Gate Bipolar Transistors (IGBTs). IGBTs are power semiconductor devices used in switching applications such as traction motor control, and switched-mode power supplies (SMPS). Five IGBTs were aged with a squared signal at gate and one was aged with DC waveforms (Celaya et al., 2009). The experiments were stopped after thermal runaway or latch-up failures were detected. Collector current, gate voltage, collector-emitter voltage, and package temperature measurements are given as indirect health indicators.

There are five run-to-failure samples under the same conditions. The dataset owners also declared that they experienced several problems with aging systems (Sonnenfeld et al., 2008). Thus, it is difficult to claim that the dataset could be employed for data-driven prognostics effectively.

The Coffin-Manson model (Eq. 12) is used as a physics-based model for thermal cycling applications (Cui, 2005). It is a function of temperature parameters and Arrhenius term $(G(T_{max}))$. Arrhenius term is evaluated when the maximum temperature (T_{max}) is reached in each cycle. Temperature parameters to be used in the model are given with the dataset. The dataset was therefore found to be eligible for employing a physics-based approach.

Coffin-Manson Model
$$\boldsymbol{N = Af^{-a}\Delta T^{-b}G(T_{max})} \qquad \textbf{(12)}$$ $$\boldsymbol{G(T_{max}) = exp^{((E_A/K)(1/T_{max}))}} \qquad \textbf{(13)}$$
$\boldsymbol{N = number\ of\ cycles\ to\ fail}$ $\boldsymbol{f = cycling\ frequency}$ $\boldsymbol{A = scaling\ factor}$ $\boldsymbol{\Delta T = temperature\ range\ during\ a\ cycle}$ $\boldsymbol{a = cycling\ frequency\ exponent}$ $\boldsymbol{b = temperature\ range\ exponent}$ $\boldsymbol{T_{max} = Maximum\ temperature\ reached\ in\ cycle}$ $\boldsymbol{G(T_{max}) = Arrhenius\ term}$ $\boldsymbol{E_A = Activation\ energy}$ $\boldsymbol{K = Boltzman's\ constant}$

Table 3. Physics-based models for temperature cycling

3.2. Virkler Fatigue Crack Growth Dataset

Structural health monitoring (SHM) is the process of implementing damage identification for typically civil, aerospace or mechanical engineering infrastructure (Farrar and Worden, 2007). In the SHM field, fatigue cracks are defined as one of the primary structural damage mechanisms caused by cyclic loadings. Cracks at the structure surface grow gradually. Once a crack has reached the critical length (determined by standards), the structure will suddenly fracture and it may cause the system to fail catastrophically. Therefore prediction of fatigue life or fatigue crack growth in structures is necessary.

The Virkler fatigue crack growth dataset (Virkler et al., 1979) contains 68 run-to-failure specimens. Specimens used for experiments are center cracked sheets of 2024-T3 aluminum. Each specimen had a notch of 9mm initial crack length and experiments were stopped once the crack lengths reached about 50 mm. The crack length information is provided as a direct health indicator of the specimens and is given in the dataset. Each specimen has 164 crack length observation points as shown in Figure 4. However indirect sensory measurements such as vibration, acoustic emission etc. is not provided.

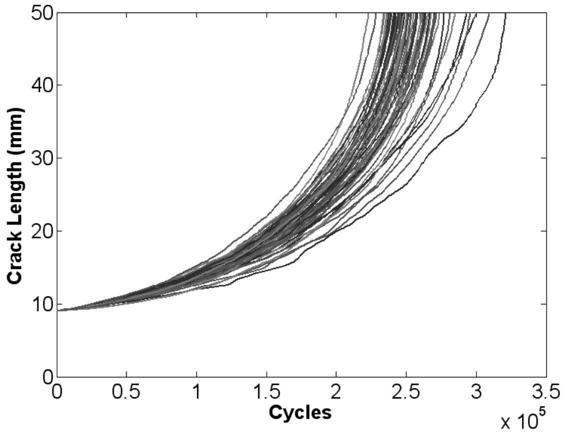

Figure 4. Crack length propagation samples under the same loading conditions

The Virkler dataset is eligible for data-driven and physics based prognostics, since there are sufficient run-to-failure samples and crack growth equations compared to prognostic dataset sample sizes mentioned in section 2. Sixty eight samples are sufficient to develop data-driven methods. Crack growth formulation as shown in Eqs. 14 and 15 can easily be used in physics based prognostics (Paris and Erdogan, 1963: Cross et al., 2006). The Paris & Erdogan crack growth rate ($\frac{da}{dN}$) formula consists of the material specific constants ($C \text{ and } m$) and the range of intensity factor (ΔK) where ($\Delta\sigma$) is range of cyclic stress amplitude, (Y) geometric constant, and (a) is crack length.

$$\frac{da}{dN} = C(\Delta K)^m \tag{14}$$

$$\Delta K = \Delta\sigma Y\sqrt{\pi a} \tag{15}$$

Challenge and requirement analysis of six different dataset has been performed both considering data-driven and physics-based modeling demands. As a result, it's found to be 4 out of 6 datasets can be modeled employing a physics-based approach easily while only two of them are applicable for a data-driven prognostics approach.

A summary table of all datasets is shown in Table 4. Compared to other datasets, the Virkler dataset was found to be the most applicable considering the requirements of both data-driven and physics-based approaches.

Dataset	Data-Driven Modeling	Physics-based Modeling
Milling Dataset	Hard	Applicable
Bearing Dataset	Hard	Hard
Battery Dataset	Hard	Applicable
Engine Dataset	Applicable	Hard
IGBT Dataset	Hard	Applicable
Virkler Dataset	Applicable	Applicable

Table 4. Prognostic approach applicability table

4. CONCLUSION

Physics-based and data-driven models are two major prognostic approaches which have been employed in several case studies found in the literature. This paper attempts to conduct requirement analysis for prognostic methods and reports the challenges of applying the two major approaches into different datasets. In general, physics-based models require the presence of a mathematical representation of the physics of failure degradation and the parameters used in degradation modeling. Data-driven models require statistically sufficient run-to-failure samples. Several datasets were examined both considering physics-based and data-driven approaches and eligibility of datasets are summarized. The Virkler dataset was found to be the most suitable with the data-driven and physics-based models. The Virkler dataset has therefore been selected to be used in a hybrid prognostic approach in the future.

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Omer Faruk Eker is a PhD student in School of Applied Sciences and works as researcher at IVHM Centre, Cranfield University, UK. He received his B.Sc. degree in Mathematics from Marmara University and M.Sc. in Computer Engineering from Fatih University, Istanbul, Turkey. He got involved in a project funded by TUBITAK, and Turkish State Railways. His research interests include failure diagnostics and prognostics, condition based maintenance, pattern recognition and data mining.

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Ian Jennions Ian's career spans over 30 years, working mostly for a variety of gas turbine companies. He has a Mechanical Engineering degree and a PhD in CFD both from Imperial College, London. He has worked for Rolls-Royce (twice), General Electric and Alstom in a number of technical roles, gaining experience in aerodynamics, heat transfer, fluid systems, mechanical design, combustion, services and IVHM. He moved to Cranfield in July 2008 as Professor and Director of the newly formed IVHM Centre. The Centre is funded by a number of industrial companies, including Boeing, BAe Systems, Rolls-Royce, Thales, Meggitt, MOD and Alstom Transport. He has led the development and growth of the Centre, in research and education, over the last three years. The Centre offers a short course in IVHM and the world's first IVHM MSc, begun in 2011.

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