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A Copula-based Sampling Method for Data-driven Prognostics and Health Management

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ABSTRACT

This paper develops a Copula-based sampling method for data-driven prognostics and health management (PHM). The principal idea is to first build statistical relationship between failure time and the time realizations at specified degradation levels on the basis of off-line training data sets, then identify possible failure times for on-line testing units based on the constructed statistical model and available on-line testing data. Specifically, three technical components are proposed to implement the methodology. First of all, a generic health index system is proposed to represent the health degradation of engineering systems. Next, a Copula-based modeling is proposed to build statistical relationship between failure time and the time realizations at specified degradation levels. Finally, a sampling approach is proposed to estimate the failure time and remaining useful life (RUL) of on-line testing units. Two case studies, including a bearing system in electric cooling fans and a 2008 IEEE PHM challenge problem, are employed to demonstrate the effectiveness of the proposed methodology.

Keywords: prognostics and health management, data-driven, remaining useful life, Copula

1. INTRODUCTION

To support critical decision-making processes such as maintenance replacement and system design, activities of health monitoring and life prediction are of great importance to engineering systems composed of multiple components, complex joints, and various materials. Stressful conditions (e.g., high pressure, high temperature, and high irradiation field) imposed on these systems are the direct causes of damage in their integrity and functionality, which necessitates the continuous monitoring of these systems due to the health and safety concerns [1-3]. Research on real-time diagnosis and prognosis which interprets data acquired by distributed sensor networks, and utilizes these data streams in making critical decisions provides significant advancements across a wide range of applications for minimizing the cost [4-6], maximizing the availability [7] and extending the service life [8]. For instance, in nuclear power plants, unexpected breakdowns can be prohibitively expensive and disastrous since they immediately result in lost power production, increased maintenance cost, reduced public confidence, and, possibly, human injuries and deaths. In order to reduce and possibly eliminate such problems, it is necessary to accurately assess current system health condition and precisely predict the residual useful lives (RULs) of operating components, subsystems, and systems in the high-risk engineering systems.

In general, prognostics approaches can be categorized into model-based approaches [9-14], data-driven approaches [15-26] and hybrid approaches [27-31]. Model-based approaches rely on the understanding of system physics-of-failure and underlying system degradation models. Myötyri et al. [9] proposed the use of a stochastic filtering technique for real-time RUL prediction in the case of fatigue crack growth while considering the uncertainties in both degradation processes and condition monitoring measures. A similar particle filtering approach was later applied to condition-based component replacement in the context of fatigue crack growth [10]. Orchard et al. [11] proposed a combination of rescaled

Epanechnikov kernel functions to estimate the RUL where the system state parameter was estimated by a particle filtering approach. Luo et al [12] developed a model-based prognostic technique that relies on an accurate simulation model for system degradation prediction and applied this technique to a vehicle suspension system. Gebraeel presented a degradation modeling framework for RUL predictions of rolling element bearings under time-varying operational conditions [13] or in the absence of prior degradation information [14]. As practical engineering systems generally consist of multiple components with multiple failure modes, understanding all potential physics-of-failures and their interactions for a complex system is almost impossible. With the advance of modern sensor systems as well as data storage and processing technologies, the data-driven approaches for system health prognostics, which are mainly based on the massive sensory data with less requirement of knowing inherent system failure mechanisms, have been widely used and become popular. A good review of data-driven prognostic approaches was given in [15]. Mahalanobis distance (MD) was proposed for failure detection and prediction associated with a curve fitting approach to fit the degradation feature [16-17]. A Bayesian updating approach was developed for the RUL prediction of on-line test units on the basis of linear and nonlinear modeling of the degradation feature [18-19]. Heimes [20] proposed to use recurrent neural networks (RNNs) for the RUL prediction. Emmanuel and Rafael [21] recommended a methodology for handling lack of information of the training degradation data using a combination of information theory, neuro-fuzzy system, and Dempster-Shafer theory. A similarity-based approach [22] was developed for estimating the RUL in prognostics where rich run-to-failure data are available and later was adopted in [23] with a novel fuzzy definition of trajectory pattern similarity for the RUL prediction of a nuclear system. Medjaher et al. [24] proposed to use mixture of Gaussians hidden Markov models to identify the best model and its parameters for the RUL prediction. Other than individual model and algorithm, an ensemble approach of various models and algorithms was also studied for data-driven prognostics [25-26]. Hybrid approaches attempt to take advantage of the strength from data-driven approaches as well as model-based approaches by fusing the information from both approaches [27-31]. Similar to model-based approaches, the application of hybrid approaches is limited to the cases where sufficient knowledge on system physics-of-failures is available.

Implicit relationship between the RUL and sensory signals makes it difficult to know which prognostic algorithm performs the best in a specific application. Furthermore, there are many factors that affect the RUL prediction accuracy and robustness, such as 1) dependency of the algorithm's accuracy on the amount of training units, 2) unit-to-unit variability and large uncertainties in environmental and operational conditions, 3) the amount of effective sensory signals for the RUL prediction, and 4) form of the degradation trend (e.g., linear, nonlinear, noisy, smooth). Thus, techniques and methodologies for health prognostics are generally application-specific. This paper proposes a Copula-based sampling method for the RUL prediction, in which the relationship between sensory signals and the failure time is explicitly built using various Copulas. The proposed method is a new data-driven prognostics approach that is accurate and robust for the RUL prediction and applicable for diverse engineering systems. Two case studies, including a bearing system in electric cooling fans and a 2008 IEEE PHM challenge problem, are employed to demonstrate the effectiveness of the proposed methodology. The rest of the paper is organized as follows. Section 2 elaborates the Copula-based sampling method with three subsections: 1) a generic health index system, 2) Copula-based modeling, and 3) the RUL prediction. Section 3 demonstrates the proposed method with two examples. Finally the conclusion is made in Section 4.

2. COPULA-BASED SAMPLING METHOD

In data-driven prognostics approach, a set of run-to-failure training units are typically required in order to build or fit a model for the system degradation, where the degradation feature or trend is extracted from raw sensory signals using signal processing techniques. This section focuses on elaboration of the Copula-based sampling method for building the system degradation model and predicting the RUL of on-line test units.

2.1 A generic health index system

Successful implementations of prognostic algorithms require the extraction of the health condition signatures and background health knowledge from massive training/testing sensory signals from engineered system units. To do so, this study uses a generic health index system that is composed of two distinguished health indices: physics health index (PHI) and virtual health index (VHI). In general, the PHI uses a dominant physical signal as a direct health metric and is thus applicable only if sensory signals are directly related to physics-of-failures. In the literature, most engineering practices of health prognostics are based on various PHIs, such as the battery impedance [32], the magnitude of the vibration signal [33] and the radio frequency (RF) impedance [34]. In contrast, the virtual health index (VHI) is applicable even if sensory signals are not directly related to system physics-of-failures. In this study, the VHI system is employed which transforms the multi-dimensional sensory signals to one-dimensional VHI with a linear data transformation method [22]. The VHI system is detailed in what follows.

Suppose there are two multi-dimensional sensory data sets that represent the system healthy and failed states, $\mathbf{Q}_0$ of $M_0 \times D$ matrix and $\mathbf{Q}_1$ of $M_1 \times D$ matrix, respectively, where M_0 and M_1 are the data sizes for system failed and healthy states, respectively, and D is the dimension of each dataset. With these two data matrices, a transformation matrix $\mathbf{T}$ can be obtained to transform the multi-dimensional sensory signal into the one-dimensional VHI as

$$\mathbf{T} = \left(\mathbf{Q}^T\mathbf{Q}\right)^{-1}\mathbf{Q}^T\mathbf{S}_{\text{off}} \tag{1}$$

where $\mathbf{Q} = [\mathbf{Q}_0; \mathbf{Q}_1]$, $\mathbf{S}_{\text{off}} = [\mathbf{S}_0, \mathbf{S}_1]^{\text{T}}$, $\mathbf{S}_0$ is a $1 \times M_0$ zero vector and $\mathbf{S}_1$ is a $1 \times M_1$ unity vector. This transformation matrix $\mathbf{T}$ can transform any sensory signal from the offline learning or online prediction process to the normalized VHI as $\mathbf{H} = \mathbf{Q}_{\text{off}} \cdot \mathbf{T}$ or $\mathbf{H} = \mathbf{Q}_{\text{on}} \cdot \mathbf{T}$, where $\mathbf{Q}_{\text{off}}$ and $\mathbf{Q}_{\text{on}}$ are the offline and online multi-dimensional sensory data sets, respectively, and, if we assume the data sizes for $\mathbf{Q}_{\text{off}}$ and $\mathbf{Q}_{\text{on}}$ are respectively M_{on} and M_{off} (i.e., $\mathbf{Q}_{\text{off}}$ of $M_{\text{off}}\times D$ matrix and $\mathbf{Q}_{\text{on}}$ of $M_{\text{on}}\times D$ matrix), $\mathbf{H}$ will be a column vector of the size M_{off} or M_{on}. The VHI can also be denoted as $h(t_i)$ for $i = 1,\ldots, M_{\text{off}}$ (for the offline case) or for $i = 1,\ldots, M_{\text{on}}$ (for the online case), varying approximately between 0 and 1. This VHI can be used to construct background health knowledge (e.g., predictive health degradation curves) in the offline training process and to further conduct the online prediction process.

The health index is further processed with Savitzky-Golay smoothing filters [35] to smooth the noisy signal. In this study, we assume that the processed health index should be non-decreasing with respect to the time. In other words, health condition of the system will only become worse as time goes by. Thus, the smoothed health index is further processed to maintain the non-decreasing property. For example, the health index at the i^{th} time step will be replaced by the index at the $(i-1)^{\text{th}}$ time step if the former is less than the later.

2.2 Copula-based modeling

2.2.1 Discretization of the health index

The health index is discretized into a certain number of degradation levels. For M number of training data sets, the i^{th} degradation level is defined as

$$y_i = y_1 + \frac{(i-1)(y_N - y_1)}{(N-1)};$$
$$\text{where } y_1 = \min_M(\mathbf{y}_0) \text{ and } i = 1, \ldots, N \tag{2}$$

where y_N is the N^{th} degradation level which is defined as the failure threshold; $\mathbf{y}_0$ is a vector of initial health index from M number of training data sets. According to the Eq. (2), a time realization matrix $\mathbf{T}$ can be identified in Eq. (3).

$$\mathbf{T} = \begin{bmatrix} t_{11} & \cdots & t_{1j} & \cdots & t_{1M} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ t_{i1} & \cdots & t_{ij} & \cdots & t_{iM} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ t_{N1} & \cdots & t_{Nj} & \cdots & t_{NM} \end{bmatrix} = \begin{bmatrix} t_{1\bullet} \\ \vdots \\ t_{i\bullet} \\ \vdots \\ t_{N\bullet} \end{bmatrix} \tag{3}$$

where t_{ij} indicates the time realization at the i^{th} degradation level for the j^{th} training data. T_i is defined as a random variable standing for the random time realization at the i^{th} degradation level. Thus, the matrix $\mathbf{T}$ is readily used for the statistical dependence modeling of the time realization at different degradation levels.

A Copula is a general way in statistics to formulate a multivariate distribution, particularly for a bivariate distribution, with various statistical dependence patterns. Determination of the best Copula based on the available random samples of the multivariate distribution is typically conducted in two steps: i) selection of the optimal marginal distribution; and ii) determination of an optimal Copula.

2.2.2 Selection of the optimal marginal distribution

Maximum Likelihood Estimation (MLE) is used to select the optimal marginal distribution for the time realization at the i^{th} degradation level. The statistics of the random variable T_i is represented by the statistical parameter Θ of a candidate distribution. For example, in the case of a normal distribution, the parameter is defined as $\Theta=\{\mu_\theta, \sigma_\theta\}$, which includes the mean and standard deviation of T_i. Thus, Θ is the calibration parameter and needs to be identified. The statistical model calibration using MLE is formulated as

$$\text{Maximize } L(T_i \mid \Theta) = \sum_{j=1}^{M} \log_{10}\left[f(t_{ij} \mid \Theta)\right] \tag{4}$$

where $L(\cdot)$ is the likelihood function and $f(\cdot)$ is the Probability Density Function (PDF) of T_i for a given Θ. A candidate distribution pool, including Normal, Lognormal, Weibull, Beta, Gamma, and Uniform, is defined and the optimal marginal distribution is determined by the maximum likelihood value among candidate distributions.

2.2.3 Determination of the optimal Copula

A Copula is a joint distribution function of standard uniform random variables. According to Sklar's theorem [36], there exists an n-dimensional Copula C such that for all T in a real random space

$$F(T_1, \ldots, T_N) = C(F_1(T_1), \ldots, F_N(T_N)) \tag{5}$$

where F is an N-dimensional distribution function with marginal functions $F_1, \ldots, F_N$. To this date, most Copulas only deal with bivariate data due to the fact that there is a lack of practical n-dimensional generalization of the coupling parameter [37,38]. For multivariate data, a usual approach is to analyze the data pair-by-pair using two-dimensional Copulas. The common methods to select the optimal Copula are based on the maximum likelihood approach [39-41], which relies on the estimation of an optimal parameter set. Recently a Bayesian Copula approach [37] was proposed to select the optimal Copula that is independent on the parameter estimation. It was further shown in their study that this approach provides more reliable identification of true Copulas even with the lack of samples [37]. Hence, the Bayesian Copula approach is employed for the statistical dependence modeling of time realizations at different degradation levels. For the sake of completeness, we briefly describe the procedures for selecting the optimal Copula using the Bayesian approach. Interested readers should refer to the reference [37] for details.

A set of hypotheses are first made as follows using the Bayesian Copula approach.

H_k : The data come from Copula C_k, $k = 1, \ldots, Q$

The objective is to find the Copula with the highest probability, $Pr(H_k \mid D)$, from a finite set of Copulas, where D represents the bivariate data in the standard uniform space. Based on the Bayes' theorem, probability that the bivariate data come from the Copula C_k is expressed as

$$\Pr(H_k \mid D) = \frac{\Pr(D \mid H_k)\Pr(H_k)}{\Pr(D)} = \int_{-1}^{1} \frac{\Pr(D \mid H_k, \tau)\Pr(H_k \mid \tau)\Pr(\tau)d\tau}{\Pr(D)} \tag{6}$$

where τ is the Kendall's tau, which is a non-parametric measure of the statistical dependence associated to Copulas. The probability of Kendall's tau, Pr(τ), is equally likely for each Copula. All Copulas are equally probable with respect to a given τ which reflects no preference over the Copulas. The likelihood Pr($D|H_k$, τ) depends upon τ and can be calculated from the Copula PDF as

$$\Pr(D \mid H_k, \tau) = \prod_{l=1}^{M} c_k(u_{1l}, u_{2l} \mid \tau) \tag{7}$$

where c_k (•) is the PDF of the k^{th} Copula; M is the total number of bivariate data; u_{1l} and u_{2l} are the l^{th} bivariate data. The normalization of Pr (D) can be computed using the sum rule [42]. Four representative Copulas (Clayton, Gaussian, Frank, and Gumbel) are employed in this study.

2.2.4 Copula modeling of the time realization matrix

Copula modeling is only performed between the time realization at the i^{th} and the N^{th} degradation level (or the defined failure time) because the objective is to predict the failure time (or the residual useful life) of the engineering system provided that we know some actual time realizations at a certain number of degradation levels. Therefore, N-1 times of bivariate Copula modeling are required in the proposed approach. In summary, four steps are conducted for the Copula modeling of the time realization matrix.

Step 1: Random variable T_i to describe the time realizations at the i^{th} degradation level is transformed into the standard uniform space (or U-space) based on the optimal marginal distribution obtained in Section 2.2.2.

Step 2: Bayesian Copula modeling is performed between the random variable T_i and T_N in the U-space.

Step 3: Sufficient random samples of the optimal Copula are generated in the U-space.

Step 4: Random variable T_i is transformed from the U-space back to the original random space (or X-space).

It should be noted that the time realization at the N^{th} degradation level must be larger than or equal to the time at the i^{th} degradation level (i.e. $T_N \geq T_i$ for $i<N$) because it takes time for the system to decay. This property, however, is not guaranteed in the Copula modeling. Hence, semi-Copula model is proposed to impose such requirement by eliminating samples of $T_N<T_i$ after the step 4. The semi-Copula model is a truncated Copula model and can be expressed in Eq. (8).

$$C(u_i, u_N) = C(F_i(T_i), F_N(T_N)), \text{ where } T_N \geq T_i \text{ for } i<N \tag{8}$$

2.3 RUL prediction

Figure 1 shows a flowchart of the RUL prediction for a given test unit. First of all, raw signals are processed to obtain the health index up to the time for RUL prediction using the proposed generic health index system. Next, training data sets that have the same initial health condition as the test unit are selected for Copula-based modeling. The initial health condition can be determined from the VHI value with a certain percentage of tolerance (e.g. 10%) to account for the signal noise. Finally, actual time realizations of the test unit at corresponding degradation levels are identified and they are used for the RUL prediction.

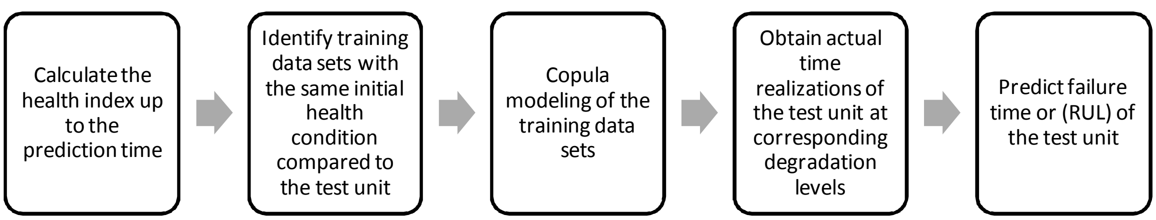


Figure 1: Flowchart of the RUL prediction for a test unit

Prediction of failure time or the RUL is essentially a process to identify possible time realizations at the N^{th} degradation level provided that we know some true time realizations at a certain number of degradation levels. Mathematically, it is a process to identify a conditional PDF of T_N, $f(T_N|T_i)$, given that $T_i = a_i$. The health index of a new test unit may have experienced several defined degradation levels such that multiple true time realizations are knonwn for the T_i where i ranges from 1 to j. Theoretically, it is feasible to obtain such a conditional PDF of T_N if a joint PDF $f(T_1, \ldots T_j, T_N)$ is available. In reality, however, only bivariate joint PDFs of T_i and T_N are contructed using Copulas. Hence, Eq. (9) is used to approximate the conditional PDF of T_N.

$$f(T_N \mid T_1 = a_1, T_2 = a_2, \ldots, T_j = a_j) \cong \beta \prod_{i=1}^{j} f(T_N \mid T_i = a_i) \tag{9}$$

where β is a normalization parameter such that integration of the PDF equals to one. It is aware that the conditional PDF of T_N could be an arbitrary distribution. Although it is feasible to calculate the analytical solution of T_N based on Eq. (9), its mathematical expression could be lengthy. Instead, estimation of the mean and standard deviation of T_N is the key point of interest for the RUL prediction. Hence, a sampling approach is proposed to estimate the mean and standard deviation of T_N with following five steps.

i. Generate same number of failure time samples (e.g. $T_{N,1}$, $T_{N,2}$, …, $T_{N,j}$) from j conditional PDFs in Eq. (9), where $T_{N,i}$ indicates the failure time samples generated from $f(T_N|T_i=a_i)$;

ii. Identify lower (T_{N_lower}) and upper (T_{N_upper}) bounds of the failure time from j sets of samples, where

$$T_{N\_lower} = \max\left[\min(T_{N,1}), \min(T_{N,2}), \ldots, \min(T_{N,j})\right]$$
$$T_{N\_upper} = \min\left[\max(T_{N,1}), \max(T_{N,2}), \ldots, \max(T_{N,j})\right]$$

iii. Filter out samples located outside the identified bounds;

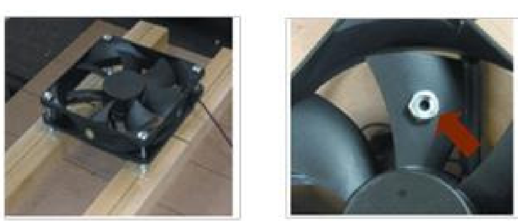
iv. Calculate the mean, standard deviation, and empirical PDF of the failure time from remaining samples;

v. Compute the mean, standard deviation, and empirical PDF of the RUL.

3. EXAMPLES

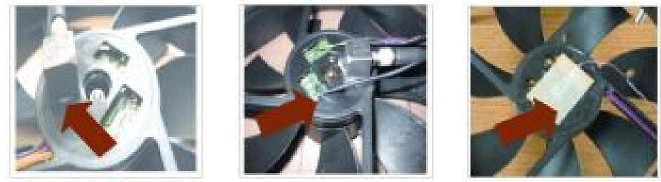
3.1 RUL prediction of electric cooling fans

Cooling fans are one of the most critical parts in system thermal solution of most electronic products and have been a major failure contributor to many electronic systems [43]. This study aims to demonstrate the proposed methodology with 32 run to failure electronic cooling fans. In this experimental study, thermocouples and accelerometers were used to measure temperature and vibration signals. To make time-to-failure testing affordable, the accelerated testing condition for the fans was sought with inclusion of a small amount of tiny metal particles into ball bearings and an unbalanced weight on one of the fan blades. The fans were tested with 12V regulated power supply and three different signals were measured and stored in a PC through a data acquisition system. Fig. 2 (a) shows the test fixture with 4 screws at each corner for the fan units. As shown in Fig. 2 (b), an unbalanced weight was used and mounted on one blade for each fan. Sensors were installed at different parts of the fan, as shown in Fig. 3. In this study, three different signals were measured: the fan vibration signal from the accelerometer, the Printed Circuit Board (PCB) block voltage, and the temperature measured by the thermocouple. An accelerometer was mounted to the bottom of the fan with superglue, as shown in Fig. 3(a). Two wires were connected to the PCB block of the fan to measure the voltage between two fixed points, as shown in Fig. 3(b). As shown in Fig. 3(c), a thermocouple was attached to the bottom of the fan and measures the temperature signal of the fan. Vibration, voltage, and temperature signals were acquired by the data acquisition system and stored in PC. The data acquisition system from National Instruments Corp. (NI USB 6009) and the signal conditioner from PCB Group, Inc. (PCB 482A18) were used for the data acquisition system. All fans were tested at the same initial health condition and run till failure.



(a) (b)

Figure 2: Test configuration of the cooling fans



(a) (b) (c)

Figure 3: Sensor installations for a fan test, (a) accelerometer (b) voltage measurement (c) thermocouples

3.1.1 Physical health index (PHI)

The sensory signal screening found that the fan PCB block voltage and the fan temperature did not show clear degradation trend, whereas the vibration signal showed health degradation behavior. This study involved the root mean squares (RMS) of the vibration spectral responses at the first five resonance frequencies and defined the RMS of the spectral responses as the degradation signals for the life prediction. Among 32 fan units, Fig. 4 shows the RMS signals of 3 fan units to demonstrate the health degradation behavior. The RMS signal gradually increases as the bearing in the fan degrades over time. It was found that the degradation signals are highly random and non-monotonic because of metal particles, sensory signal noise, and input voltage noise. For the RUL prediction, the first 20 fan units were employed for the training data sets, while the rest were used as the testing data sets for the online RUL prediction.

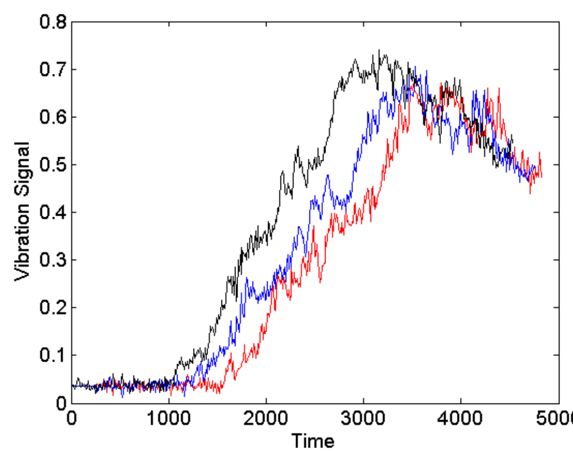


Figure 4: Vibration signal of three fans

The vibration signals (or PHI) were further processed with Savitzky-Golay smoothing filters to smooth the noisy signals and maintain the non-decreasing property of the PHI for 20 training data sets. Figure 5 shows such signal processing for one PHI of a training fan unit. Data discretization was then conducted to obtain a 50×20 time realization matrix where N=50 and y_{50}=0.60. According to the defined failure threshold, failure time ranges from 2681 minutes to 3441 minutes for 20 training data sets.

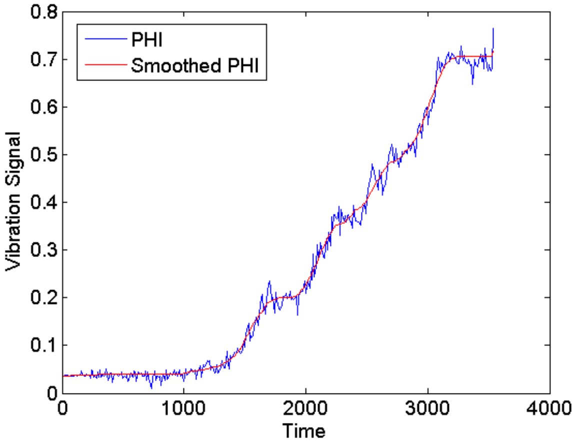
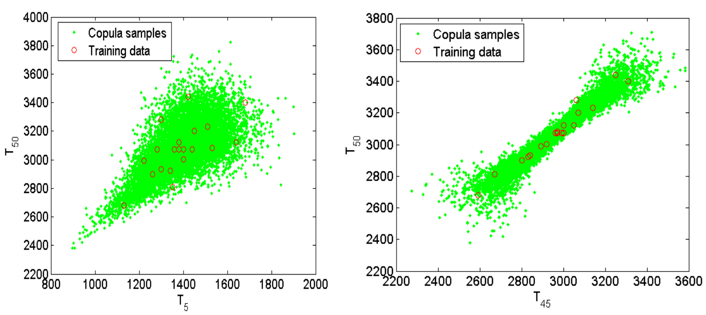


Figure 5: Signal processing of a PHI

3.1.2 Copula-based modeling

Copula modeling was performed between two random variables of T_i and T_{50}, where i =1, 2,…, 49. Figure 6 shows two such optimal Copulas for i equals to 5 and 45, respectively. Statistical dependence between T_i and T_{50} can be clearly observed for both cases. Specifically, a Clayton Copula was selected in Fig. 6(a) with a correlation parameter equals to 1.74 and a Frank Copula was chosen in Fig. 6(b) with a correlation parameter equals to 35.77. Each Copula sample stands for one possible time realization at the i^{th} and 50th degradation levels. It is aware that some Copula samples may not be physically meaningful because $T_i > T_{50}$. Hence, semi-Copula models were actually employed by eliminating the Copula samples that are not physically meaningful.



(a) Clayton Copula (b) Frank Copula

Figure 6: Copula modeling of T_i and T_{50}

3.1.3 RUL prediction

The fan unit #21 (or the test unit #1) was used as an example to illustrate the RUL prediction after operation of 1500 minutes. The vibration signal was smoothed and processed to have non-decreasing property. According to the defined degradation levels, the test unit #1 has experienced 4 degradation levels as shown in Fig. 7(a). Four conditional PDFs of the failure time were obtained on the basis of Copula modeling and the actual time realization at four degradation levels. Same amount of failure time samples were generated from each conditional PDF with identified lower (T_{N_lower}) and upper (T_{N_upper}) bounds as 2730 and 3601, respectively. The samples located outside the bounds were filtered out and empirical PDFs of the failure time and the RUL were obtained based on the remaining samples. Figure 7(b) shows the failure time prediction at operation time of 1500 minutes, where all possible failure times are projected to the 50th degradation level (the failure threshold). Figure 7(c) shows the comparison of RUL prediction where the true RUL is slightly larger than the mean of the model prediction. Similarly, RULs of the test unit #1 were effectively calculated at different operating times. Figure 7(d) shows the comparison between the true and predicted RULs, where the solid line stands for the true RUL, the cycles indicate the mean of the RUL from model prediction at twenty operating times, and the crosses denote the 95% confidence level of the model prediction.

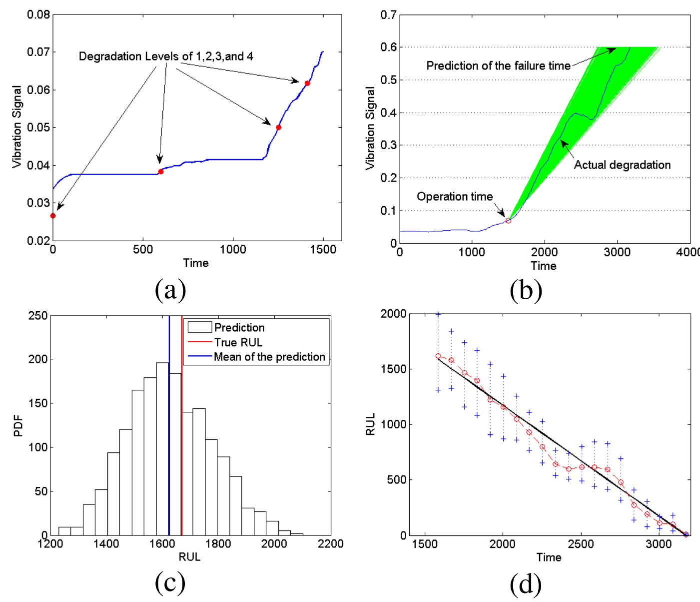


Figure 7: RUL prediction of the test unit #1

The RUL prediction for rest eleven test units was conducted and the comparison was made between the true RUL and the mean RUL from the model prediction. Figure 8 lists the results for twelve test units, where the solid line stands for the true RUL and circles denote the mean RUL from the model prediction. Generally speaking, the RUL prediction is more accurate as more degradation signal is collected. Although the mean RUL from the model prediction could be either overestimated or underestimated in contrast with the true RUL, it presents quite well alignment with the true RUL especially when the unit is close to the failure. It is noticed that the predicted RUL is consistently underestimated for unit #7 and unit #9. Further investigation reveals that the unit #7 and #9 exhibit abnormal degradation behavior in contrast with the training data as shown in Fig. 9. It is expected that such error can be alleviated by including these degradation behavior in the training data sets.

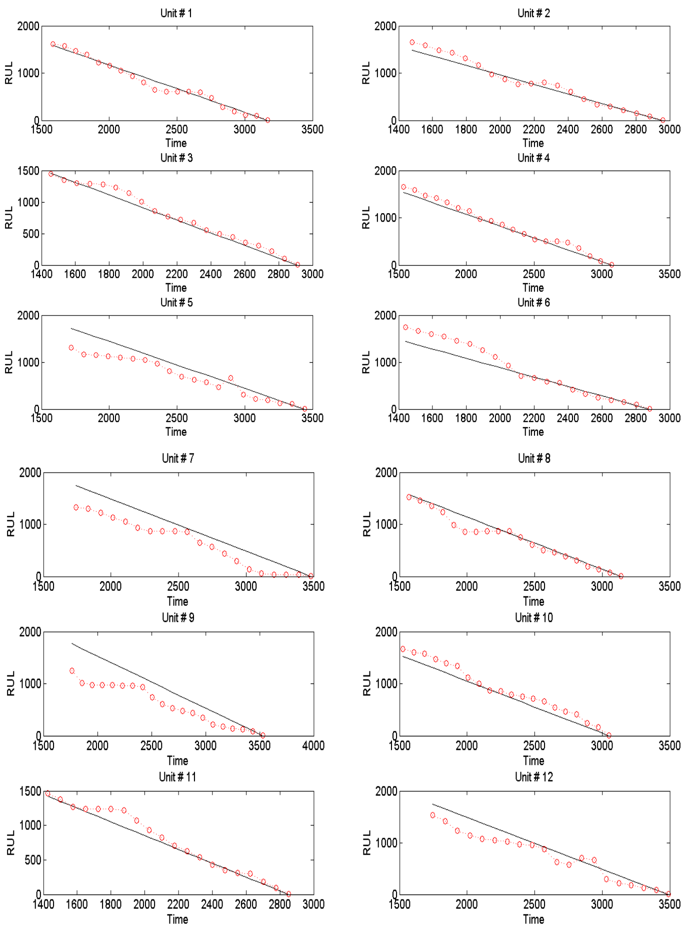


Figure 8: Comparison of the RUL prediction for 12 test units

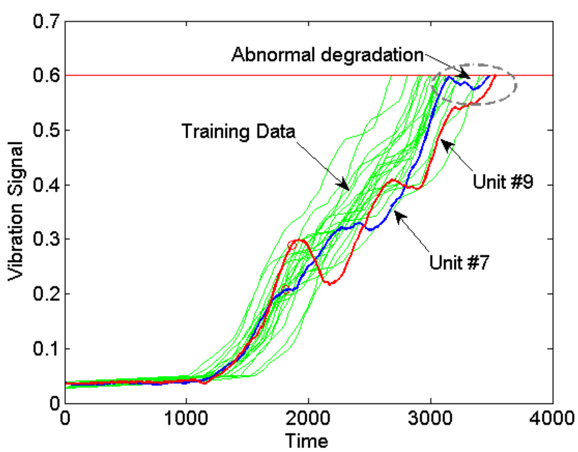


Figure 9: Abnormal degradation of the unit #7 and #9 in contrast with the training data

3.2 2008 IEEE PHM challenge problem

In an aerospace system (e.g., an airplane, a space shuttle), system safety plays an important role since failures can lead to dramatic consequences. In order to meet stringent safety requirements as well as minimize the maintenance cost, condition-based maintenance must be conducted throughout the system's life time, which can be enabled by system health prognostics. This case study aims at predicting the RULs of aircraft engine systems in an accurate and robust manner with massive and heterogeneous sensory data.

3.2.1 Problem description

The data set provided by the 2008 IEEE PHM challenge problem consists of multivariate time series signals that are collected from an engine dynamic simulation process. Each time series signal comes from a different degradation instance of the dynamic simulation of the same engine system [44]. The data for each cycle of each unit include the unit ID, cycle index, 3 values for an operational setting and 21 values for 21 sensor measurements. The sensor data were contaminated with measurement noise and different engine units start with different initial health conditions and manufacturing variations which are unknown. Three operational settings have a substantial effect on engine degradation behaviors and result in six different operation regimes as shown in Table 1. The 21 sensory signals were obtained from 6 different operation regimes. The whole data set was divided into training and testing subsets, each of which consists of 218 engine units. In the training data set, the damage growth in a unit was allowed until the occurrence of a system failure when one or more limits for safe operation have been reached. In the testing data set, the time series signals were pruned some time prior to the occurrence of a system failure. The objective of the problem is to predict the number of remaining operational cycles before failure in the testing data set.

Table 1: Six different operation regimes

Regime ID	Operating parameter 1	Operating parameter 2	Operating parameter 3
1	0	0	100
2	20	0.25	20
3	20	0.7	0
4	25	0.62	80
5	35	0.84	60
6	42	0.84	40

Among the 21 sensory signals, some signals contain no or little degradation information of an engine unit whereas the others do. To improve the RUL prediction accuracy, important sensory signals must be carefully selected to characterize the degradation behavior of engine units for health prognostics. Following the work in [22], this study selected 7 sensor signals (2, 3, 4, 7, 11, 12 and 15) among the 21 sensory signals for constructing the VHI. The evaluation metric considered for this example employed an asymmetric score function around the true RUL such that heavier penalties are placed on late predictions [44]. The score evaluation metric S is expressed as

$$S\left(\hat{L}_i, L_i^T\right) = \begin{cases} \exp\left(-d_i/13\right)-1, & d_i < 0 \\ \exp\left(d_i/10\right)-1, & d_i \geq 0 \end{cases} \quad \text{where } d_i = \hat{L}_i - L_i^T \qquad (10)$$

where $\hat{L}_i$ and L^T denote the predicted and true RUL of the i^{th} unit, respectively.

3.2.2 Virtual health index (VHI)

Based on the selected 7 sensor signals, the VHI was built to represent degradation of the engine health state. Different transformation matrix $\boldsymbol{T}_k$ must be constructed using Eq. (1) at different operation regimes (k=1,2,…,6). Correspondingly, $\mathbf{Q}_0$ and $\mathbf{Q}_1$ matrices can be built at different operation regimes. For the VHI construction, the system healthy matrix $\mathbf{Q}_0$ was created using the sensor data in a system healthy condition, $0 \le L \le 4$, while the system failure matrix $\mathbf{Q}_1$ using those in a system failure condition, $L > 300$, where L indicates the number of operating cycles. Different $\mathbf{Q}_0$ and $\mathbf{Q}_1$ were created by repeating this process for 6 operating regimes. As shown in Table 2, a 7×6 transformation matrix is constructed using Eq. (1), in which each column is a transformation vector for the corresponding operation regime.

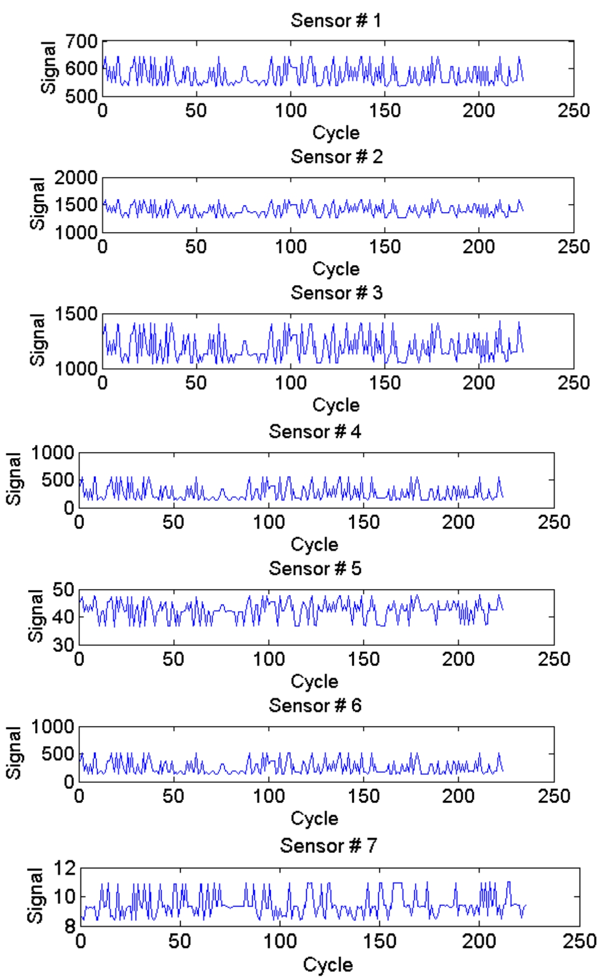


Figure 10: Raw sensor signals of the training unit #1

VHI was then calculated for 218 training and testing data sets and further processed to maintain the non-decreasing property as described in Section 2.1. Figure 10 shows 7 sensor signals of the training unit #1 before constructing the VHI. It is difficult to observe the engine degradation with mixture of 6 operation regimes and multi-dimensional signals. In contrast with raw sensor signals, Fig. 11 shows the VHI of the training unit #1, in which a clear degradation path is presented.

Table 2: Transformation matrix (**T**) for VHI

Regime 1	Regime 2	Regime 3	Regime 4	Regime 5	Regime 6
0.0263	-0.0045	-0.0055	-0.0500	-0.0406	-0.0590
0.0040	0.0032	0.0062	0.0028	0.0030	0.0096
0.0059	0.0062	0.0053	0.0053	0.0057	0.0084
-0.0206	-0.0618	-0.0563	-0.0228	-0.0239	-0.0289
0.2774	0.2122	0.3017	0.2021	0.2952	0.4377
-0.0794	-0.0161	-0.0585	-0.0370	-0.0272	-0.0697
1.0047	1.2686	1.2805	1.9235	1.0643	0.5491

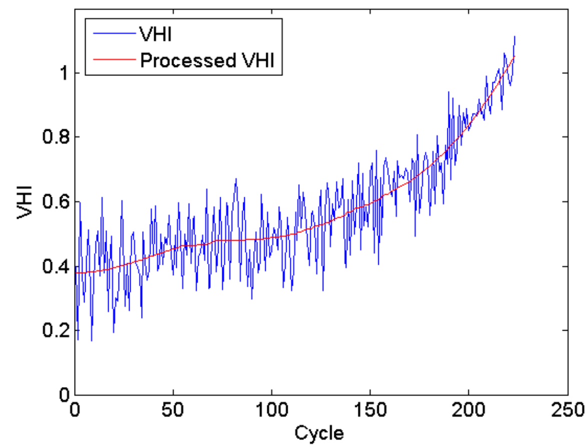


Figure 11: VHI of the training unit #1

3.2.3 Results of RUL prediction

It is aware that the initial health condition should be different for 218 training data sets because the processed VHI ranges from 0.1124 to 0.5802. Hence, it is important to identify the training data sets that possess the same or similar initial health condition compared to the test unit for accurate RUL prediction. In this case study, if the initial VHI difference (or the maximum VHI difference at the first 5 cycles) between a training and test unit is less than 10% tolerance, they were considered to have a similar initial health condition. As a consequence, different amount of training data sets were identified for different test units. Thus, Copula-base modeling was adaptively executed for different test units. Figure 12 shows the identified training data sets for the test unit #1. RUL prediction of the test unit #1 was then calculated as 95 cycles. Compared to the true RUL of 122 cycles, score loss of 6.84 was computed using Eq. (10).

Similarly, RULs were calculated for 218 test units and the results were compared to the true RULs as shown in Fig. 13. Generally speaking, the RUL prediction is more accurate when the test unit is close to failure. Large prediction variance is observed when the test unit possesses large RULs. An average score loss was calculated as 8.12 for 218 test units.

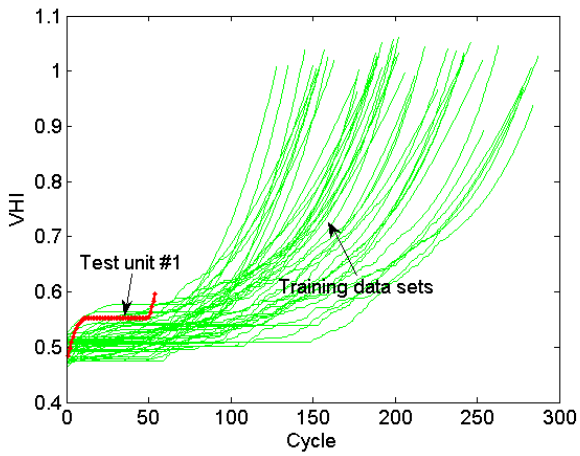


Figure 12: Training data sets for the test unit #1

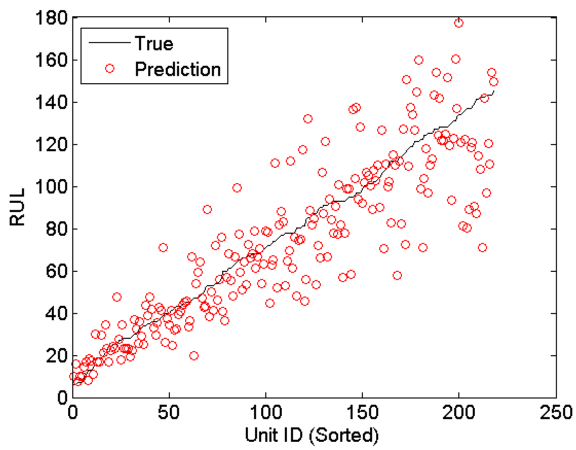


Figure 13: RUL comparison for 218 test units

4. CONCLUSION

This paper proposed a Copula-based sampling method as a data-driven prognostic approach for the RUL prediction of engineering systems under uncertainty. A generic health index system was employed so that health degradation of engineering systems can always be represented by a one-dimensional and non-decreasing degradation curve. Copula-based modeling was proposed to build a generic statistical relationship between failure time and time realizations at specified degradation levels. This approach is generic and applicable to any linear or nonlinear degradation signals. In other words, the proposed approach does not require any assumption for the form of degradation signals. A sampling approach was finally proposed to effectively predict the failure time and RUL of engineering systems. It approximates a multi-dimensional condition PDF of the failure time using multiple bivariate conditional PDFs. Two examples, the bearing system in electric cooling fans and a 2008 IEEE PHM challenge problem, were employed to demonstrate the effectiveness of the proposed data-driven prognostics. The results of two case studies indicate that accuracy of the proposed methodology is comparable to other state-of-the-art prognostics methodologies with a new mechanism for the RUL prediction.

5. ACKNOWLEDGEMENT

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