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Differential evolution-based multi-objective optimization for the definition of a health indicator for fault diagnostics and prognostics

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ABSTRACT

The identification of the current degradation state of an industrial component and the prediction of its future evolution is a fundamental step for the development of condition-based and predictive maintenance approaches. The objective of the present work is to propose a general method for extracting a health indicator to measure the amount of component degradation from a set of signals measured during operation. The proposed method is based on the combined use of feature extraction techniques, such as Empirical Mode Decomposition and Auto-Associative Kernel Regression, and a multi-objective Binary Differential Evolution (BDE) algorithm for selecting the subset of features optimal for the definition of the health indicator. The objectives of the optimization are desired characteristics of the health indicator, such as monotonicity, trendability and prognosability. A case study is considered, concerning the prediction of the remaining useful life of turbofan engines. The obtained results confirm that the method is capable of extracting health indicators suitable for accurate prognostics.

1. Introduction

Condition-based and predictive maintenance approaches can increase safety, minimize downtimes, and ensure mission completion and efficient production [45,9,15,71,5]. To enable this, it is necessary to estimate the current degradation state of the components and systems of interest, and predict the future evolution.

In recent years, diagnostic approaches for the identification of equipment degradation using signal measurements have been proposed and successful industrial applications have been performed [59,58,82]. Furthermore, prognostic approaches have been developed for the prediction of equipment remaining useful life (RUL), i.e. the amount of time that the equipment will continue to perform its function according to specifications [60–62,66,52,71].

Health Indicators (HIs) are introduced in fault diagnostic and prognostic approaches, to measure the amount of equipment degradation. Depending on the equipment and its degradation mechanism, the HI can be a signal directly measured or not.

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Examples of directly measurable degradation indicators are the length of a crack in a structure [44,8,55,40], the light output from fluorescent light bulbs or the thickness of a car tyre tread [15]. Measurement noise can affect the raw data obtained from the sensors, possibly obscuring the signal trend; for this reason, filtering techniques are applied to smooth the HI. For example, many approaches rely on Bayesian methods, e.g. Kalman and particle filters, to infer equipment degradation using signal measurements and a physics-based model of the degradation process.

Examples in which a direct measure of the equipment degradation is not available are bearing wear [81,82] and various other mechanisms such as stiction, wear, contamination and degradation of dielectrics in Micro-Electro Mechanical Systems (MEMS) [53]. In these cases, it is necessary to extract a HI from the available measurements, which are not directly related to the component degradation state. Although several HIs have been developed for fault diagnostics and prognostics of different types of industrial components, the solutions already proposed are typically not general, but tailored to the component and the characteristics of the monitored signals.

Typically, HI extraction is performed by (i) pre-processing the raw data to reduce the measurement and process noises and (ii) extracting degradation trends using statistical indicators in the time domain, such as mean and standard deviation, and other indicators in the frequency or time-frequency domains [46,33,4,10].

In [38], Empirical Mode Decomposition (EMD) is used to extract information about the evolution of degradation over time. The main idea is that a time-dependent signal can be described as fast oscillating components superimposed to slow oscillating ones. The residual of this approximation is the trend of the signal, whose variations can show the degradation evolution over time. In [13], an approach based on the use of the Auto-Associative Kernel Regression (AAKR) has been used for the extraction of health indicators. The AAKR empirical model receives in input the current signal value and reproduces in output the value that the signal is expected to have in healthy conditions, before the beginning of the degradation (signal reconstruction). The residual, i.e. the difference between the signal measured value and the AAKR reconstruction, defines the HI.

Once a set of features has been extracted from the raw measurements, it can be useful to combine them into a single degradation indicator, since individual features may contain only partial (and different) information about the equipment degradation state. In [13], a HI is defined as a linear combination of AAKR residuals of different signals. The coefficients of the linear combination are obtained by a genetic algorithm optimization whose objectives are the three metrics of *Monotonicity*, *Trendability* and *Prognosability*, which assess the capability of a HI of properly quantifying the equipment degradation. In [67], an approach based on Principal Component Analysis (PCA) and Hidden Markov Models (HMM) is proposed for the definition of a HI for prognostics.

The objective of the present work is to propose a systematic and general method for the construction of a HI. Since the approach should be applicable to signals obtained from industrial components of different nature, we consider various signal extraction techniques, including statistical indicators, EMD, wavelet and Fourier transforms.

The proposed method differs from previous literature approaches in the technique used for combining the extracted features. Differently from [13], which linearly combines multiple residuals obtained from several AAKR models, each one reconstructing a single measured signal, we define the HI as the residual of an AAKR model which reconstructs in a single step a group of features. The idea behind this approach is that features that individually do not have the characteristics of health indicators may provide useful information when considered jointly with other features. For example, a feature related to the component operating conditions can drive the computation of the residuals of features related to the component degradation and also influenced from the operating conditions.

A large number of features can be extracted from the measured signals and several different combinations (subsets) of them can be selected: then, the definition of a HI can be seen as the problem of selecting the best combination of features to be used. The approach that we explore in this work to address this problem is based on a multi-objective optimization that considers as objectives the metrics of *Monotonicity*, *Trendability* and *Prognosability*. The multi-objective optimization provides a number of Pareto-optimal solutions, which are non-dominated with respect to the considered objectives [10].

We resort to a Binary Differential Evolution (BDE) algorithm for the multi-objective optimization. The choice of BDE is due to the fact that it explores the decision space more efficiently than other multi-objective evolutionary algorithms [57], including Non-dominated Sorting Genetic Algorithm II (NSGA-II) [16], Strength Pareto Evolutionary Algorithm 2 (SPEA2) [72] and Indicator Based Evolutionary Algorithm (IBEA) [74].

The main novelties of the proposed approach are:

- the use of EMD as a feature extraction method and not for directly building a HI, as in [38];
- the use of an AAKR model to combine different features into a HI;
- the BDE multi-objective search for the selection of the optimal HI.

An application is considered, concerning the prediction of the RUL of a fleet of turbofan engines working under variable operating conditions. Data describing the evolution of 21 signals during the engine run-to-failure trajectories have been taken from the NASA Ames Prognostic Data Repository [50]. The obtained results have been compared to those obtained by (1) directly considering one of the measured features as HI, (2) applying the method in [38], where the EMD features are directly used as HIs.