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Remaining useful life estimation in heterogeneous fleets working under variable operating conditions

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ABSTRACT

The availability of condition monitoring data for large fleets of similar equipment motivates the development of data-driven prognostic approaches that capitalize on the information contained in such data to estimate equipment Remaining Useful Life (RUL). A main difficulty is that the fleet of equipment typically experiences different operating conditions, which influence both the condition monitoring data and the degradation processes that physically determine the RUL. We propose an approach for RUL estimation from heterogeneous fleet data based on three phases: firstly, the degradation levels (states) of an homogeneous discrete-time finite-state semi-markov model are identified by resorting to an unsupervised ensemble clustering approach. Then, the parameters of the discrete Weibull distributions describing the transitions among the states and their uncertainties are inferred by resorting to the Maximum Likelihood Estimation (MLE) method and to the Fisher Information Matrix (FIM), respectively. Finally, the inferred degradation model is used to estimate the RUL of fleet equipment by direct Monte Carlo (MC) simulation. The proposed approach is applied to two case studies regarding heterogeneous fleets of aluminium electrolytic capacitors and turbofan engines. Results show the effectiveness of the proposed approach in predicting the RUL and its superiority compared to a fuzzy similarity-based approach of literature.

1. Introduction

Prognostics of failures aims at forecasting the Remaining Useful Life (RUL) of an equipment, i.e., the amount of time the equipment can continue performing its functions under its design specifications [1–4]. Knowledge of the RUL would allow avoiding system unscheduled shutdowns by defining efficient maintenance strategies that exploit the full RUL for operation. This would increase the system availability and safety, while reducing maintenance costs [2,4,5]. For these attractive reasons, there is an increasing interest of industry for failure prognostics [3,6,7].

Approaches for RUL estimation can be generally categorized into model-based and data-driven [2,8–13]. Model-based approaches use physics models to describe the degradation behaviour of the equipment [4,9,14,15]. For example, Li et al. [16,17], have proposed two prediction models of defect propagation in bearings; Oppenheimer et al. [18], have modelled a rotor shaft crack growth using the Forman law of linear elastic fracture mechanics and used the model for predicting its health condition and, correspondingly, estimating its RUL; Di Maio et al. [19], have explored the combination of exponential regression and Relevance Vector Machines (RVMs) for estimating the RUL of partially degraded thrust ball bearings; Cadini et al. [20], have used Particle Filtering (PF) for estimating the RUL of equipment subject to fatigue crack growth; modelled by Paris-Erdogan law [21], and for defining the optimal policy of condition-based equipment replacement. Despite the fact that these approaches lead to accurate prognostics results, uncertainty arising due to the assumptions and simplifications of the adopted models may pose limitations on their practical deployment [3,9,22–24].

Contrarily, data-driven prognostics approaches do not use any explicit physical model, but rely exclusively on the availability of process data related to equipment health to build (black-box) models that capture the degradation and failure modes of the equipment [4,23]. For example, Di Maio et al. [22], have introduced a data-driven fuzzy similarity-based prognostics approach for estimating the RUL of equipment subject to fatigue cycles; Recurrent Neural Networks (RNNs) [25], Neuro-Fuzzy (NF) systems [26] and Support Vector Machines (SVMs) [27] have also been used for prognostics, with success. In spite of the recognized potential of

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Nomenclature

RUL	Remaining Useful Life
RNNs	Recurrent Neural Networks
RVMs	Relevance Vector Machines
PF	Particle Filtering
SVMs	Support Vector Machines
NF	Neuro-Fuzzy
HDTFSSMM	Homogeneous Discrete-Time Finite-State Semi-Markov Model
MLE	Maximum Likelihood Estimation
FIM	Fisher Information Matrix
MC	Monte Carlo simulation
N_{max}	Number of Monte Carlo simulation trials
FCM	Fuzzy *C*-Means
CSPA	Cluster-based Similarity Partitioning Algorithm
P	Number of equipment in the fleet
$P_{training}$	Number of equipment used for training
$P^{c}_{training}$	Number of complete-run-to-failure trajectories used for training
$P^{ic}_{training}$	Number of incomplete-run-to-failure trajectories (right-censored) used for training
P_{test}	Number of equipment used for testing
p	Index of equipment, p=1, …,$P_{training}$ and/or P_{test}
$\theta=\{q, \beta\}$	Parameters of the discrete Weibull distribution
$\hat{\theta}=\{\hat{q}, \hat{\beta}\}$	Estimated parameters of the discrete Weibull distribution
H	Number of base clusterings
j	Index of base clustering
C^{j}_{opt}	Optimum number of clusters of the j-th base clustering
PPI	Prognostic Performance Indicator
S	Number of degradation states (final consensus clusters) of equipment
S_{final}	Number of degradation states including the failure state of equipment
i	Index of degradation state, $i = 1, \ldots, S_{final}$
$\bar{\bar{X}}$	Dataset matrix of the collected measurements
$C_{candidate}$	Possible number of clusters in the final consensus clustering$S$, $C_{candidate} \in [C_{min}, C_{max}]$
RMSE	Root Mean Square Error for prognostics
AI	Accuracy Index for prognostics
α–λ accuracy	$(\alpha - \lambda)$ accuracy index for prognostics
PI	Precision Index for prognostics
CR	Coverage Rate for prognostics
$RUL_p(t_l)$	True RUL of p-th equipment at the measurement time t_l
$\widehat{RUL}_p(t_l)$	Estimated RUL of p-th equipment at the measurement time t_l
I_p	Number of measurements of p-th equipment
Z	Number of signals of each degradation trajectory
z	Index of signal
$t^{(p)}_l$	Index of the measurement time of p-th equipment, $l = 1, \ldots, I_p$
M	Number of discrete time steps between two successive measurements
$ESR^{measured}$	Measurements of the degradation indicator
T	Temperature profiles experienced by the capacitors
ESR^{norm}	Capacitors degradation indicator
DB	Davies-Bouldin criteria
$c^{p}_{t_l}$	Coverage value of p-th equipment at the measurement time t_l
$(\alpha - \lambda)^{p}_{t_\lambda}$	$(\alpha - \lambda)$ value of p-th equipment at the measurement time t_λ
$w^{p}_{t_l}$	Width value of p-th equipment at the measurement time t_l
m_p	The monotonicity of the p-th degradation trajectory, $p = 1, \ldots, P_{training}$

these data-driven approaches, challenges still exist for their practical applications [4,22]:

1) to build accurate models, data-driven approaches require sufficiently representative run-to-failure data (i.e., time series data up to the threshold value beyond which the equipment loses its functionality) which, in some practical cases, might be expensive or impractical to obtain; for this reason, data-driven approaches are more commonly applied for equipment of relatively short life than for safety-critical and slow-degrading equipment, for which complete run-to-failure trajectories are rarely available [4,28];
2) these approaches are computationally intense [4];
3) with these models it is difficult to provide a measure of confidence on the RUL predictions, i.e., the uncertainty affecting the predictions [22,29];
4) these approaches do not provide a clear physical interpretation of the current degradation condition of the equipment under observation, i.e., they behave like black-boxes [30].

To overcome these challenges, it seems worthwhile to consider and make use of the knowledge and data coming from similar equipment, forming what in the industrial context is called a fleet [6,31], rather than relying solely on the knowledge and data coming from a single equipment. This will improve our knowledge concerning the equipment behaviour, reduce prognostics uncertainty and, thus, improve the efficiency of the fault prognostics task. A fleet of P pieces of equipment might:

1) have identical technical features and usage, and work in the same operating conditions, thus forming an identical fleet, e.g., a fleet of identical diesel engines located in one ship [6]; knowledge derived from a fleet of this nature has been used for defining thresholds for anomaly detection [32] and for diagnosing faults [33] of equipment identical to the fleet members;
2) share some technical features and work in similar operating conditions, but show differences either on some features or on their usage, forming a so-called homogenous fleet, e.g., a fleet of trains working over a common route [34]; knowledge derived from this type of fleet has been used for developing diagnostics approaches for enhancing maintenance planning [34];
3) have different and/or similar technical features, but undergo different usage with different operating conditions, forming a so-called heterogeneous fleet, e.g., a fleet of highly standardized steam turbines of pressurized water reactors nuclear power plants [35]; this type of fleet can provide wider knowledge concerning the equipment behaviour [6,31,36].

The variability of behaviour of the members of the different types of industrial fleet above mentioned gives rise to a variability in a population of elements, in mathematical terms.

Most of the existing fleet-wide approaches for failure prognostics treat only the information gathered from identical and/or the homogenous fleets rather than from heterogeneous ones [14].

The objective of the present work is to develop a data-driven