Technical Report on the solution of the CMAPSS-RUL dataset using Neural Networks

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Abstract

In this report we present an a data-driven approach for estimating the Remaining Useful Life (RUL) of aero-engines. A "strided" time window approach is employed to generate training and test sets to be used with a conventional Multi-layer Percepton (MLP) which will serve as the main regressor for this application, no model for the engine is required . The proposed approach is evaluated on the publicly available C-MAPSS dataset. The accuracy of the proposed method is compared against other state-of-the art methods available in the literature.

Index terms— Artificial Neural Networks (ANN), Moving Time Window, RUL Estimation, C-MAPSS, Prognostics

1. Introduction

Traditionally, maintenance of mechanical systems has been carried out based on scheduling strategies, nevertheless strategies such as breakdown corrective maintenance and scheduled preventive maintenance are often costly and less capable of meeting the increasing demand of efficiency and reliability [1, 2]. Condition Based Maintenance (CBM) also known as intelligent Prognostics and Health Management (PMH) allows for maintenance based on the current health of the system, thus cutting costs and increasing the reliability of the system [3]. To avoid confusion, here we define prognostics as the estimation of remaining useful component life. The Remaining Useful Life (RUL) of a system can be estimated based on history trajectory data, this approach which we refer here as data-driven can help improve maintenance schedules to avoid engineering failures and save costs [4]. This paper proposes a Machine Learning (ML) approach for RUL estimation.

The existing PMH methods can be grouped into three different categories: model-based approaches [5] , data-driven approaches [6, 7] and hybrid approaches [8, 9].

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Model-based approaches attempt to incorporate physical models of the system into the estimation of the RUL. If the system degradation is modeled precisely, model-based approaches usually exhibit better performance than data-driven approaches [10], nevertheless this comes at the expense of having extensive a prior knowledge of the underlying system and having a fine-grained model of such system (which usually involve expensive computations). On the other hand data-driven approaches tend to use pattern recognition to detect changes in system states. Data-driven approaches are appropriate when the understanding of first principles of system operation is not comprehensive or when the system is sufficiently complex (i.e. jet engines, car engines, complex machinery) such that developing an accurate model is prohibitively expensive. Common disadvantages for the data-driven approaches are that they usually exhibit wider confidence intervals than model-based approaches and that a fair amount of data is required for training. Many data-driven algorithms have been proposed and good prognostics results have been achieved, among the most popular algorithms we can find Artificial Neural Networks (ANN) [11], Support Vector Machine (SVM) [12], Markov Hidden Chains (MHC) [13].

Over the past few years, data-driven approaches have gained more attention in the PMH community. A number of machine learning techniques, especially neural networks have been successfully applied to the estimate RUL of diverse mechanical systems. ANNs have demonstrated good performance when applied for modeling highly nonlinear, complex, multi-dimensional system without any prior expertise on the system's physical behavior [14]. While the confidence limits for the RUL predictions can not be naturally provided [15], the neural network approaches are promising on prognostic problems.

In this paper we propose a Multi-layer Perceptron (MLP) architecture coupled with a strided time-window approach for estimating the RUL of aero-engines. The publicly available NASA C-MAPSS dataset [16]. Raw sensor measurements with normalization are directly used as inputs to the MLP which then outputs the RUL of the jet engine in terms of cycles. (Here I have to explain about the similarities between this work and Xiangs and the original time window approach, why is feature extraction not used in this work? why does this NN performs better than the ANN with FE but FE is not necessary here).

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