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Prediction of Remaining Useful Lifetime (RUL) of Turbofan Engine using Machine Learning

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ABSTRACT -
In recent years, research has proposed several deep learning (DL) approaches to providing reliable remaining useful life (RUL) predictions in Prognostics and Health Management (PHM) applications. Although supervised DL techniques, such as Convolutional Neural Network and Long-Short Term Memory, have outperformed traditional prognosis algorithms, they are still dependent on large labeled training datasets. With respect to real-life PHM applications, high-quality labeled training data might be both challenging and time-consuming to acquire. Alternatively, unsupervised DL techniques introduce an initial pre-training stage to extract degradation related features from raw unlabeled training data automatically. Thus, the combination of unsupervised and supervised (semi-supervised) learning has the potential to provide high RUL prediction accuracy even with reduced amounts of labeled training data. This paper investigates the effect of unsupervised pre-training in RUL predictions utilizing a semi-supervised setup. Additionally, a Genetic Algorithm (GA) approach is applied in order to tune the diverse amount of hyper-parameters in the training procedure. The advantages of the proposed semi-supervised setup have been verified on the popular C-MAPSS dataset. The experimental study, compares this approach to purely supervised training, both when the training data is completely labeled and when the labeled training data is reduced, and to the most robust results in the literature. The results suggest that unsupervised pre-training is a promising feature in RUL predictions subjected to multiple operating conditions and fault modes.

I. INTRODUCTION

Prognostics is an engineering discipline that works on the prediction of the future state or response of a given system based on the synthesis observations, calibrated mathematical models, and simulation [1]. It generally refers to the study of predicting the specific time at which the system will no longer be able to have its intended functional performance. Prognostics attempts to predict remaining useful life (RUL) of an engineering system of a component. Salunkhe [2] regards RUL as the time left before observing a failure. RUL is also called as remaining service life or remnant life referring to the time left before observing a failure given the current machine age, condition and the past operation profile. Okoh et al. [3] defines RUL as the time remaining for a component to perform its functional capabilities before failure. In recent years, prognostics has attracted vast attention from both academic researchers and industrial operators. For instance, according to Lei et al. [4], there is a rapid rise in publications in the area of machinery prognostics. 8th International Conference on Through-Life Engineering ServiceCase Western Reserve University, Cleveland, OH, USA. October 27-29, 2019

II. RELATED WORK

The C-MAPSS dataset has been extensively used to evaluate several DL approaches to RUL predictions. This section reviews the most recent studies applied on the C-MAPSS dataset. The selected studies either utilize a Convolutional Neural Network (CNN), a Deep Belief Network (DBN) or Long-Short Term Memory (LSTM) in the proposed deep architecture.

In most PHM applications, sequential data is a standard format of the input data, for example pressure and temperature time series data. LSTM is a well-established DL technique to process sequential data. The original LSTM [15] was developed after the early 1990s, when researchers discovered a vanishing and exploding gradient issue in traditional Recurrent Neural Networks (RNNs) [16]. This issue confirmed that traditional RNNs had difficulty learning long-term dependencies. To cope with this issue, the LSTM introduces a memory cell that regulates the information flow in and out of the cell. Consequently, the memory cell is able to preserve its state over long durations, that is learning long-term dependencies that may influence future predictions. Yuan et al. proposed an LSTM approach for several different faults [17]. The proposed approach was compared with traditional RNN, Gated Recurrent Unit LSTM (GRU-LSTM) and AdaBoost-LSTM. It showed improved performance in all cases. Another LSTM approach was provided by Zheng et al. [6]. The proposed approach provides RUL predictions using two LSTM layers, two Feed-forward Neural Network (FNN) layers, and an output layer. The LSTM layers were able to reveal hidden patterns in the C-MAPSS dataset and achieved higher accuracy compared to the Hidden Markov Model or traditional RNN. A similar study was provided by Wu et al. [18]. In this study, an LSTM was combined with a dynamic difference method in order to extract new features from several operating conditions before the training procedure. These features contain important degradation information, which improves the LSTM to better control the underlying physical process. The proposed approach showed enhanced performance compared to traditional RNN and GRU-LSTM.

Although CNNs have performed excellently on 2D and 3D grid-structured topology data, such as object recognition [20] and face recognition [21], respectively, CNNs can also be applied to 1D grid-structured topology sequential data in PHM applications. Babu et al. proposed a novel CNN approach for RUL predictions [5]. This CNN approach includes two layers with convolution and average-pooling steps, and a final FNN layer to perform RUL predictions. The proposed approach indicated improved accuracy compared to the Multilayer Perceptron (MLP), Support Vector Machine (SVM), and Relevance Vector Machine. More recently, [7] takes a CNN approach. In this study, Li et al. achieved even higher accuracy on the C-MAPSS dataset compared to both the LSTM approach in [6] and the CNN approach in [5]. They employed the recently developed, proven regularization technique "dropout" [11] and the adaptive learning rate method "adam" [10].

Hinton et al. introduced the greedy layer-wise unsupervised learning algorithm in 2006, designing it for DBNs [22]. A DBN consists of stacked Restricted Boltzmann Machines (RBMs) where the hidden layer in the previous RBM will serve as the input layer for the current RBM. The algorithm performs an initial unsupervised pre-training stage to learn internal representations from the input data automatically. Next, supervised fine-tuning is performed to minimize the training objective. Zhang et al. have proposed a multiobjective DBN ensemble approach [19]. This approach combines a multiobjective evolutionary ensemble learning framework with the DBN training process. Accordingly, the proposed approach creates multiple DBNs of varying accuracy and diversity before the evolved DBNs are combined to perform RUL predictions. The combined DBNs are optimized through differential evolution where the average training error is the single objective. The proposed approach outperformed several traditional machine learning algorithms, such as SVM and MLP.

III. EXISTING AND PROPOSED SYSTEMS

In recent years, research has proposed several deep learning (DL) approaches to providing reliable remaining useful life (RUL) predictions in Prognostics and Health Management (PHM) applications. Although supervised DL techniques, such as Convolutional Neural Network and Long-Short Term Memory, have outperformed traditional prognosis algorithms, they are still dependent on large labeled training datasets. With respect to real-life PHM applications, high-quality labeled training data might be both challenging and time-consuming to acquire. Alternatively, unsupervised DL techniques introduce an initial pre-training stage to extract degradation related features from raw unlabeled training data automatically. Thus, the combination of unsupervised and supervised (semi-supervised) learning has the potential to provide high RUL prediction accuracy even with reduced amounts of labeled training data. This paper investigates the effect of unsupervised pre-training in RUL predictions utilizing a semi-supervised setup. Additionally, a Genetic Algorithm (GA) approach is applied in order to tune the diverse amount of hyper-parameters in the training procedure. The advantages of the proposed semi-supervised setup have been verified on the popular C-MAPSS dataset. The experimental study, compares this approach to purely supervised training, both when the training data is completely labeled and when the labeled training data is reduced, and to the most robust results in the literature. The results suggest that unsupervised pre-training is a promising feature in RUL predictions subjected to multiple operating conditions and fault modes.

Maintenance of equipment is a critical activity for any business involving machines. Predictive maintenance is the method of scheduling maintenance based on the prediction about the failure time of any equipment. The prediction can be done by analyzing the data measurements from the equipment. Machine learning is a technology by which the outcomes can be predicted based on a model prepared by training it on past input data and its output behavior. The model developed can be used to predict machine failure before it actually happens. There are different approaches available for developing a machine learning model. In this paper, a comparative study of existing set of machine learning algorithms to predict the Remaining Useful Lifetime of aircraft's turbo fan engine is done. The machine learning models were constructed based on the datasets from turbo fan engine data from the Prognostics Data Repository of NASA. Using a training set, a model was constructed and was verified with a test data set. The results obtained were compared with the actual results to calculate the accuracy and the algorithm that results in maximum accuracy is identified. We have selected ten machine learning algorithms for comparing the prediction accuracy. The different algorithms were compared to obtain the prediction model having the closest prediction of remaining useful lifecycle in terms of number of life cycles.

IV. DEEP LEARNING APPROACHES

Deep learning is one of the sub-branches of machine learning which is featured by multiple nonlinear processing layers, and originated from artificial neural network (ANN). As the rapid development of computational infrastructure, DL has become one of the main research topics in the field of prognostics, given its capability to capture the hierarchical relationship embedded in deep structures [22]. The characteristic of DL is its deep network architecture where multiple layers are stacked in the network to fully capture the representative information from raw input data [23]. DL models have gained great attention and remarkable achievement in many fields, such as image recognition [24], speech recognition and natural language processing [25]. However, it has not been fully exploited in the field of RUL prediction [26]. The published literature on DL mainly focused on four representative deep architectures, including Auto-encoder, Deep Belief Network (DBN), Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) [27]. This section aims to review the start-of-the-art based on these four representative deep architectures. 2.1. Auto-encoder Auto-encoder (AE) can learn a new representation of the data through reconstructing the input data, which contains two phases: encoder and decoder. Thus, it is often used for pre-training of network. The stacked sparse auto-encoder (SAE) is one of the most commonly used deep neural network (DNN) approaches dealing with the data because it contains multilayer AE like sparse auto-encoder and denoising AE [28]. In machine health monitoring, AE models are majorly used for fault diagnostics. For RUL prediction, AE is normally used to extract degradation features, very limited direct applications of AE on RUL prediction can be found in literature. For instance, Ramin et al. [29] developed a novel prognostic method for machine bearings called auto-encoder-correlation-based (AEC) prognostic algorithm. They collected some test-to-failure experiments sensory data and extracting unsupervised features by training a spare AE. Then, a moving average filter was used to pass through the output. The health condition of the system can be illustrated after the AEC algorithm normalizes the output of the filter. Jian et al. [28] predicted that the RUL of an aircraft engine using a stacked SAE combined with logistic regression (LR). The stacked SAE was used to extract performance degradation features and fuse multiple features through multilayer self-learning. Although the authors claimed that the RUL was predicted based on a stacked SAE, it was actually achieved by an LR model. Lei et al. [30] developed a deep learning based prediction framework to predict the RUL of bearings combining deep AE and DNN. The deep AE was used to select bearing degradation features and reduce the number of prediction network parameters. 2.2. Deep Belief Network Deep Belief Network (DBN) is a stack of Restricted Boltzmann Machines (RBMs) which includes Boltzmann Machines (BMs) with a single layer of feature detecting units and higher-order BMs [31]. The greedy layer-by-layer learning algorithm of RBMs can pre-train the model in an unsupervised way with no strict demand on the amount of training data. Liao et al. [32] proposed an enhanced RBM with a novel regularization term to generate features for RUL prediction automatically. Their work was to fill the research gap of regularizing the RBM model to output a feature space that can highly represent a degradation pattern. Zhang et al. [33] presented a multi-objective deep belief networks ensemble (MODBNE) model for the RUL estimation, which employs a powerful multi-objective evolutionary algorithm (EA) based on the decomposition integrated with the traditional DBN training technique. The proposed approach can evolve multiple DBNs simultaneously, subject to two conflicting objectives: accuracy and diversity. Ma et al. [22] applied Discriminative deep belief network with ant colony optimization(ACO-DDBN) to predict health status of the machine. DDBD utilizes a deep architecture to combine the advantages of DBN and discriminative ability of back-propagation strategy. The ACO can discover the best parameter combinations when selecting the parameters for DDBN. The structure of DDBN model is determined automatically without prior knowledge through optimization. Deutsch and He[34] presented a DBN-feedforward neural network (DBN-FNN) algorithm to predict RUL of rotating components using vibration sensor. They developed DBN-FNN approach combines the advantages of the self-taught feature learning capability of the DBN and the predicting ability of the FNN, which can either take processed vibration features or extract features from the vibration data for predicting the RUL. Although the RUL prediction performance of DBF-FNN was not as good as that of the particle filter, the proposed method accomplished the objective of automatic feature extraction and RUL prediction without the intervention of human in the age of big data. Deutsch et al. [35] then developed a new integrated method that combined a DBN with a particle filter for RUL prediction of hybrid ceramic bearings using vibration signals. Real vibration data of hybrid ceramic bearing run-to-failure tests were collected and used to validate the proposed prognostic approach. The proposed integrated approach presents a better RUL prediction performance than the particle filter-based approach and the RBN method. 2.3. Convolutional Neural Network Convolutional Neural Network (CNN) is a multi-layer feedforward ANN, firstly put forward by LeCun [36], focusing on two-dimensional inputs such as image, using stacking convolutional layers and pooling layers to achieve the features learning. It was then widely well recognized for its capability to reveal abstract visual features, for instance, color contrast and gradient by using the corresponding filters. Although the CNN based approaches have achieved excellent results in the machinery fault diagnosis and surface integration inspection [37], there are few research reports on their application in RUL prediction. Navathe et al. [26] developed the first CNN model which is specifically applied for solving a RUL estimation problem. It was also the first attempt to leverage deep learning approach in RUL prediction. In their work, CNN was mainly used to conduct different processing units alternatively such as convolution, pooling, sigmoid/hyperbolic tangent squashing, rectifier and normalization. The authors claimed that the proposed deep CNN based regression approach for RUL estimation is both efficient and accurate when compared with several state-of-the-art algorithms on two publicly available data sets. Inspired by this work, Li et al. [38] developed a new deep learning architecture for RUL estimation in prognostics. For improving the feature extraction by CNN, a time window approach is utilized for sample preparation. The proposed approach adopted the raw sensor measurements directly as the model inputs. They claimed that no prior expertise on prognostics and signal processing was required using this approach, which facilitates its application in the industrial area. Prognostic performance of the proposed approach was validated based on the experiments carried out on the popular C-MAPSS dataset. The experiment results of this proposed approach was compared to the CNN approach provided by Navathe et al. [26], and the LSTM approach provided by Zheng et al. [39]. The outcomes of the comparison demonstrated that the proposed approach achieves a high accuracy on the RUL prediction. Li et al. [40] developed a novel intelligent RUL prediction approach of bearings, where the time-frequency domain information was explored and the CNN was used for multi-scale feature extraction. To demonstrate the superiority of the proposed method, the rolling bearing dataset prepared from the PRONOSTIA platform was used for experiments. Furthermore, different implementations of the DNN-based approaches were compared such as DNN, Single Scale-Low (SSL) and Single Scale-High (SSH). Good prognostic results of the proposed approach suggests its potential in industrial applications. 2.4. Recurrent Neural Network Recurrent Neural Network (RNN) is a deep architecture that contains feedback connections from hidden or output layers to the preceding layers, thus it is able to process dynamic information [41]. Sequential data is a standard format of the input data such as pressure-time and temperature-time series data. While RNN is one of the most common sequential modeling techniques, it has limitations on long-term RUL

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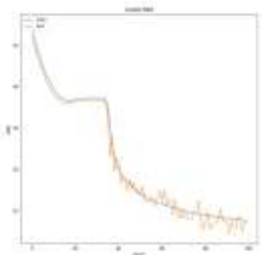
predictions because of the lack of trend identification by the weights of the trained network result from the weight updated on the presentation of each input pattern. For this reason, Long Short-Term Memory Network (LSTM), which conquers the long-term time dependency issues by controlling information flow using input gate, forget gate and output gate have been developed [39]. The RNN and its variation the Long Short-Term Memory (LSTM) networks gained great attraction in many applications which have a sequential nature. Researchers working on RUL prediction started to explore the value of RNN in this area these years, especially LSTM. Heimes [42] proposed an RNN approach to solve the IEEE 2008 Prognostics and Health Management conference challenge problem which is related to the RUL prediction of a complex system. The RNN training algorithm consists of a Truncated Back Propagation through Time gradient calculation, an Extended Kalman Filter training method and evolutionary algorithms. Yuan et al. [43] proposed a LSTM approach for diagnosis and RUL prediction of complex system like aero engine. While LSTM was only used for fault diagnosis, the RUL estimation was still based on a SVM model. Similarly, Guo et al. [44] developed a RNN based health indicator (RNN-HI) in order to enhance the accuracy of RUL prediction of bearings. However, the RUL of bearings is calculated using an exponential model with pre-set failure threshold of RNN-HI instead of the trained RNN directly. Zhao et al. [45] presented an integrated approach of CNN and bi-directional LSTM for machining tool wear prediction named Convolutional Bi-directional Long Short-Term Memory (CBLSTM) networks. CNN was firstly used to extract local robust features from the sequential input. Then, LSTM was utilized to encode temporal information. The proposed CBLSTM's capability of predicting the RUL of actual tool wear based on raw sensory data was verified with a real-life tool wear test. There are also many other researchers who have paid their attention on the applications of LSTM. Zheng [39] developed a LSTM based approach for RUL estimation using sensor data. The research investigated the hidden patterns from sensor and operational data with multiple operating conditions, fault and degradation models through combining multiple layers of LSTM cells with standard feed forward layers. The superiority of the LSTM model in RUL prediction was validated on three widely used data sets, C-MAPSS Data Set, PHM08 Challenge Data Set and Milling Data Set. Wu et al. [46] implemented vanilla LSTM networks to achieve good RUL prediction accuracy in the cases of complicated operations, working conditions, model degradations and strong noises. A Relevance Vector Machines (RVM) was used to detect the starting time of degradation and vanilla LSTM was used to calculate the RUL. The drawback of this approach is that the RUL requires labeling at every time step for each sample and some experiential knowledge is required since an appropriate threshold needs to be defined before the implementation of the Support Vector Machine (SVM.) Inspired by the Vanilla LSTM networks, Wu et al. [47] developed another LSTM network focusing on fault prognosis with degradation sequence of equipment, in which the RUL can be predicted without any pre-defined threshold. To achieve that goal, a one-hot vector was used as the input indicator from which the shutdown time was calculated by the model. Zhang et al. [48] presented a bi-directional LSTM network to discover the underlying patterns embedded in time series and track the system degradation and consequently, to predict the RUL. Nevertheless, the bi-directional LSTM network was only implemented to track the variation of health index, and the RUL was predicted by the recursive one-step ahead method. Ahmed et al. [49] built a new LSTM architecture for RUL prediction when short sequences of monitored observations were given with random initial wear. The proposed LSTM was able to predict the RUL with random starts, which makes it more suitable for real-world cases as the initial condition of physical systems is usually unknown especially in terms of its manufacturing deficiencies. A new, asymmetric objective function that penalizes late predictions rather than earlier ones was presented as well in order to ensure safer predictions.

V. RESULTS



MODEL MAE

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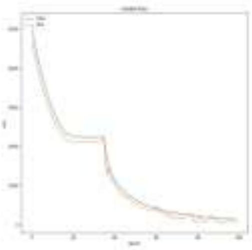
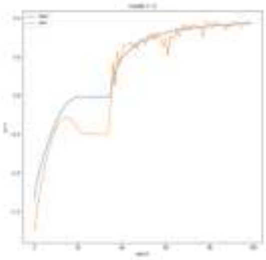
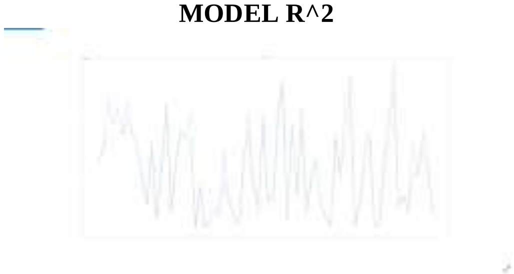


MODEL LOSS



MODEL R^2



PREDICTION

VI. CONCLUSIONS AND FUTURE WORK

The emerging infrastructure presented by the Internet of Things and data science have been a revolutionary factor in the manufacturing industry. In modern manufacturing system, RUL prediction has been increasingly important in machine health monitoring. Compared with traditional physics-based models, data-driven models gain more attention due to the significant development of sensors, sensor networks and computing systems. Machine learning techniques, especially, the DL techniques are regarded as a powerful solution due to its ability to provide a more agility to process data associated with highly nonlinear and complex feature abstraction through a cascade of multiple layers. DL provides the decision-makers new visibility into their operations, as well as real-time performance measures and costs[37]. This paper presented an overview on the latest DL-based works in the related topic covering four main DL variants: AE, DBN, CNN and RNN. It has been observed that DL-based techniques were mainly used for fault diagnostics, and very limited studies applied DL-based techniques in RUL prediction until recent years. Growth trend of literature shows an increasing interests and suggests a promising future of DL in RUL prediction. Besides, DL related RUL prediction approaches are purely data-driven approaches. Thus, in order to increase user confidence, a large database of run-to-fail trajectories should be obtained and compared to the observed data based on the similarity before the application. Additional research could be focused on combining DL approaches with other data-driven approaches or physics-based approaches because these hybrid approaches have a great potential and chance to provide a more effective and precise RUL prediction.

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