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Remaining Useful Life Prediction using Deep Learning Approaches: A Review

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Abstract

Data-driven techniques, especially on artificial intelligence (AI) such as deep learning (DL) techniques, have attracted more and more attention in the manufacturing sector because of the growth of industrial Internet of Things (IoT) and Big Data. Tremendous researches of DL techniques have been applied in machine health monitoring, but still very limited works focus on the application of DL on the Remaining Useful Life (RUL) prediction. Precise RUL prediction can significantly improve the reliability and operational safety of the industrial components or systems, avoid fatal breakdown and reduce the maintenance costs. This paper gives a brief introduction of RUL prediction and reviews the start-of-the-art DL approaches in terms of four main representative deep architectures, including Auto-encoder, Deep Belief Network (DBN), Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN). It has been observed that DL techniques attract growing interests on RUL prediction that suggests a promising future of their applications in manufacturing.

Keywords: Deep learning, Auto-encoder, Deep Belief Network, Convolutional Neural Network, Recurent Neural Network;

1. 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.

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1.1. RUL prediction approaches

RUL prediction approaches can be classified in different ways, either based on the type of available data and knowledge about the system, or according to the type of the used methodology or algorithms. In early years, the approaches were simply classified into model based (physics-based), data-driven based and hybrid based. With the increasing study in this area, more detailed classifications of the RUL prediction approaches have been proposed. The data-driven approaches are further classified into AI approaches and statistical approaches by Dawn et al [5]. Okoh et al. divided the approaches into model-based, analytical-based, knowledge-based and hybrid-based simulation algorithms and tools [3]. The model-based RUL prediction is applicable to statistics and computational intelligence approaches. The analytical-based RUL prediction methods refers to the physical failure technique. The knowledge-based RUL prediction is a combination of computational intelligence and experience. The hybrid RUL prediction is a collection methodology and technique, which can consist of any of the former approaches.

Table 1. Advantages and drawbacks of prognostic approaches

Prognostic approaches	Advantages
Physics-based approaches	• Efficient and descriptive • High Accuracy and precision • Easy to validate, certificate and verify • The dynamics of the states can be estimated at each time interval • Extrapolation outside of the training data enables more robust predictions
Data-driven approaches	• Quick implementation and deployment • Low cost of algorithms development and little knowledge requirement about system physics • Algorithms can be tuned to be used for other systems • No requirement on the assumptions and empirical estimations of physics parameters • Able to transform high-dimensional noisy data into lower dimensional information for prognostic decisions
Hybrid approaches	• Eliminate the drawbacks of physics-based approaches and data-driven approaches and gain their benefits • Do not require highly accurate models or enormous amount of data • Flexible and useful for uncertainty management through retaining the intuitiveness of the model • Higher accuracy
	Drawbacks
Physics-based approaches	• High fidelity models are costly, time consuming and computationally intensive • Limited reusability • Difficult in understanding the physics of damage for complex mechanical systems • Too stochastic and complex to model the defect • Require the examination of simplifying assumptions
Data-driven approaches	• Requirement of robust algorithm • Requirement of uncertainty management • Accuracy affected by the overgeneralization and overfitting during the training of the algorithm • Inadequate data for newly developed systems • Counter-intuitive results due to the absence of physical knowledge of the system • Require a large amount of data • Have a short prediction horizon • Low accuracy with high dimensional data
Hybrid approaches	• Carry the drawbacks of both methods but in a minor extent • Computational resource required • Require both models and data • Inaccuracy caused by incorrect model of noisy data

Physics-based approaches, also regarded as model-based approaches, assess the health of the system by building mathematical models based on the failure mechanisms or the first principle of damage [6]. Since the system degradation modelling depends on laws of nature, these approaches are generally quite efficient and descriptive. The advantage of this type of approaches are that it is relatively accurate and precise with regards to the model fidelity, ease of validation, certification and verification. While the drawbacks of these types of approaches are that building a high fidelity model for RUL prediction is expensive and time consuming, computationally intensive and with a risk of not achieving the desired outcome [7]. Moreover, even if the high fidelity models are obtained, the application could be limited only to a specific component or system, or to similar ones. For these drawbacks, the research on physics-based approaches are much less attractive than data-driven approaches.

Data-driven approaches are most widely used in the field of RUL prediction, where RUL is computed through statistical and probabilistic methods by utilizing historic information and routinely monitored data of the system [8]. The precondition for setting up the data-driven models for RUL prediction is the availability of multivariate historical data about system behavior, which must encompass all phases of the system operation and degradation scenarios under certain operating conditions. There are three ways to obtain these run to failure data: fielded applications, experimental test beds and computer simulations [7]. Although the accuracy and precision of the physics-based approaches makes them more preferred than data-driven ones, it is often very difficult to obtain a physics of failure (PoF) degradation model. In contrast, the data-driven approaches are generally user-friendly because they mainly rely on techniques from AI tools that could be applied directly or with minor modifications. The quick implementation and deployment of data-driven prognostics results in a much quicker spread speed than the physics-based ones in the RUL prediction field. Moreover, non-requirement of knowledge about the physics of the system is another main contribution to the population of these types of approaches among the prognostics system developers. The drawbacks for these types of approaches are transparent so are their advantages. Stated by Leser, a struggle extrapolation and data-generation are two of the most common difficulties highlighted in the myriad of data-driven approaches [1].

While most of the researchers concentrated on the data-driven and physics-based approaches, relatively small amount of researches focus on the hybrid approaches. Till 2017, only 8% literature in this field can be found working on hybrid prognostics approaches [4]. However, a hybrid approach can often be the better option since it attempts to integrate advantages of both physics-based and data-driven based approaches. Meanwhile, based on a certain amount of data and relatively high accurate models, a hybrid approach can usually achieve a higher accuracy for RUL prediction. Nevertheless, the drawback of the hybrid approaches are that they also carry the shortcomings of both approaches and the increased complexity in achieving the solution. Table 1 shows the comparison of these three types of approaches in terms of advantages and limitations.

1.2. Research gap

There have been considerable review papers in relation to RUL prediction. The earliest review work can be dated back to 2005 by Schwabacher [9]. His survey focused on the work in data-driven approaches for prognosis and related work in model-based and data-driven fault detection and diagnosis. Heng et al. [10] presented a brief review on the RUL prediction approaches with a specific focus on the prognostics of rotating machinery. Sikorska et al. [11] produced classification tables and process flow diagrams in order to help the industry and researchers to select the appropriate prognostic models for predicting the RUL of engineering assets. Lee et al. [12] delivered an introduction to systematic Prognostics and Health Management(PHM) design methodology, for converting data to prognostics information, which includes identifying critical components and selecting the most appropriate algorithms for specific applications. Si et al. [13] reviewed some modelling developments for estimating the RUL centered on statistical data driven approaches. Baraldi et al. [14] discussed the choice of the prognostic method in different information settings, in the RUL prediction of different prognostic approaches taking the accuracy and the ability of providing measures of confidence into consideration. Ahmadzadeh and Lundberg [15] compared some typical RUL predicting approaches based on the level of accuracy and availability of data, and discussed their advantages and disadvantages. Dawn et al. [16] provided a practical review of prognostics methods for the beginners, introducing various prognostics algorithms, and the responding pros and cons using some simple examples. Tsui et al. [17] took a holistic view to summarize mainstream methods in all major aspects of the PHM framework and their relationships, with a focus on data-driven approaches. Thamo et al. [18] reviewed the status of algorithms and methods and provided a structured and comprehensive classification of the existing state-of-the-art PHM approaches, data-driven approaches and algorithms. Huang et al. [19] summarized the problems and datasets of the PHM Data Challenge competitions, and analyzed the responding solutions and algorithms. Lei et al. [4] provided a review on machinery prognostics including all four technical processes, i.e., data acquisition, health indicator construction, health stage division and RUL prediction. Jia et al. [20] provided a review on the cutting-edge PHM methodologies and analytics based on the data competitions from 2008 to 2017, where the authors summarized the methodologies and analytics for the PHM practices in terms of failure detection, diagnosis, assessment and prediction. Gregory et al. [21] reviewed the challenges, needs, methods, and best practices for PHM within manufacturing systems, highlighting diagnostics, prognostics, dependability analysis, data management and business areas.

Considerable review works have been completed focusing on data-driven prognostics methodologies as mentioned above. Recent years, AI techniques, particularly deep learning (DL) techniques is becoming more and more attractive because of the growth in industrial Internet of Things (IoT) and Big Data. However, as one of the most cutting-edge data-driven prognostics approaches, DL based approaches have not been systematically reviewed yet. Thus, the attention of this review will be laid on the deep learning approaches focusing on the most state-of-the-art research work.

2. 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 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.

3. Conclusion

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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