PROSPECTIVE APPROACHES TO PREDICTING THE REMAINING USEFUL LIFE OF AIRCRAFT ENGINES

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Abstract. This survey covers the literature on the fault diagnosis and prediction of the remaining useful life of aircraft engines based on deep learning. A formal statement of the remaining useful life estimation problem is given. The basic architectures of deep neural networks are considered to detect rare failures and predict the next failures using aircraft engine condition monitoring data. The extraction of informative features using autoencoders is discussed. The structure of long short-term memory (LSTM) and attention mechanism (AM) cells applied in deep neural networks to predict the remaining useful life is described. The problem of integrating remaining useful life prediction into maintenance planning based on reinforcement learning is considered.

Keywords: aircraft engine diagnosis, predictive maintenance, remaining useful life prediction, deep learning.

INTRODUCTION

There are three main types of maintenance strategies: reactive, planned, and predictive maintenance. Reactive maintenance is performed after an equipment failure occurs. Aircraft engine failures can cause large economic losses, environmental damage, and, in extreme cases, even accidents [1]. Planned maintenance is a strategy under which equipment is maintained at specific intervals on a predetermined schedule, which often results in unnecessary work and associated costs. Predictive maintenance is a strategy for organizing maintenance activities according to the condition of target components or systems and the forecast of failures during operation. Predictive maintenance is a prospective maintenance technology that will improve reliability and safety while reducing maintenance costs by assessing the current state during operation and predicting the *remaining useful life* (RUL).

The predictive maintenance strategy is becoming more widespread, as it minimizes downtime and can utilize resources as efficiently as possible. Thus, reliable predictive maintenance and condition management tools are in increasing demand. Obtaining proactive condition assessment and predicting the remaining useful life of systems and/or equipment subject to aging or degradation is recognized as very important for improving the operational efficiency of aircraft and optimizing their maintenance [2]. The engine is the heart of the aircraft, being responsible for approximately 60% of all failures; therefore, diagnosing and predicting the remaining useful life of aircraft engines is critical to ensure the safe operation of the aircraft and plan maintenance works [3].

Condition-based maintenance using relevant information obtained during engine operation is performed to detect and prevent potential malfunctions and costly unplanned maintenance in due time. There are many research works on models for predicting the remaining useful life of aircraft engines [4–7]. Depending on the approaches employed, the prediction methods are divided into three groups: those based on physical models of engine degradation, those based on processing and analyzing multidimensional engine condition monitoring data, and hybrid ones [8]. The use of degradation models requires an understanding of the fundamental physical principles of engine operation and failure mechanisms [9, 10]. Given a complex relationship between sensor readings and the remaining useful life of an engine, it is very difficult to implement an adequate mathematical model of degradation. Therefore, the main studies are focused on data-driven methods, which have an advantage in the absence of an accurate mathematical model or detailed expert knowledge of the engine, and also provide the possibility of identifying unknown anomalies [11]. The data processing and analysis approach involves diagnosing the engine using collected historical operational data to predict its future condition [12–15]. A significant drawback of this approach is the non-interpretability of the models [16]. For aircraft engines used in a high-hazard industry, it is very important to ensure the interpretability of the models while maintaining predictive accuracy. Why are traditional machine learning models worse than deep learning models? To answer this question, the authors applied the *Local Interpretable Model-agnostic Explanations* (LIME) method to explain black box models [17]. An interpretable method for predicting the remaining useful life of aircraft engines under complex operating conditions using spatiotemporal characteristics was proposed in [18]. This method includes an interpretation module based on a hybrid attention mechanism for deriving interpretable predictions.

Several hybrid approaches based on physical models and data analysis were also proposed to address the problem of estimating the remaining useful life of aircraft engines. They have demonstrated promising effectiveness. Different types of hybrid architectures were presented depending on the type of information processed and the combination rules of its fragments [19].

Data-driven methods are divided into supervised (datasets contain class labels) and unsupervised (data are unlabeled). It is time-consuming and labor-intensive to obtain labeled data; therefore, unsupervised or semi-supervised methods with partially labeled data have been recently used to predict the remaining useful life to the main extent. Data-driven prediction approaches include classical machine learning methods such as Random Forest (RF), *k*-Nearest Neighbor (*k*-NN), Support Vector Machine (SVM) and its variants, Bayesian methods, Gradient Boosting (GB), etc. Recently, deep learning algorithms using autoencoders, Convolutional Neural Networks (CNNs), *Recurrent Neural Networks* (RNNs) with *Long Short-Term Memory* (LSTM), and *Gated Recurrent Unit* (GRU) cells have been increasingly investigated [20]. Bidirectional LSTM (Bi-LSTM) [21] can utilize long-range input information in two directions, from both past and future contexts. Combining a Bi-LSTM by connecting a lower-level output with an upper-level input gives a deep Bi-LSTM [22]. A challenging task is to choose, from a large number of alternatives, a particular algorithm that will produce good results in a particular situation. Many studies were devoted to comparing different approaches to solve the problem and selecting an optimal one [23].

Conventional machine learning methods require the extraction of informative features and data dimension reduction by the developer; unsuccessful data preprocessing usually results in poor performance. Deep learning algorithms can automatically extract the abstract representations of high-level functions from huge amounts of raw sensor data without the need for features extraction, inspiring more and more researchers to apply these methods to predict the remaining useful life [24]. When processing large amounts of data, a neural network handles feature extraction much better than humans [25]. Recently, deep learning models have been shown to provide very high performance when trained on large datasets due to their ability to combine automatic feature extraction with learning [26].

The operational data generated by aircraft condition sensors are highly unbalanced because engine failures occur very rarely during flight and the data are skewed towards normal operation. In this case, special analysis methods are needed to counteract the data imbalance. A rare failure detection method for predictive aircraft maintenance using a deep hybrid learning approach based on an imbalanced dataset was presented in [27, 28]. The model proposed by the authors includes two stages: the first stage involves an autoencoder to detect rare failures whereas the second stage a convolutional neural network with controlled Bidirectional Gated Recurrent Units (Bi-GRU) to predict the next occurrence of a failure. As was claimed, the model copes with irregular patterns and trends, which helps to solve the unbalanced data problem. The model consists of deep neural networks, an automatic encoder for failure detection, and bidirectional networks with ventilated recurrent units combined with convolutional neural networks to explore the relationships between variables.

In the Russian Federation, the technology of predictive modeling, particularly for the predictive maintenance of aircraft engines, is being successfully developed at the Skolkovo Institute of Science and Technology and in DATADVANCE, a company using its original software [29].

1. CONDITION MONITORING AND FAULT DIAGNOSIS OF AIRCRAFT ENGINES BASED ON DEEP NEURAL NETWORKS

1.1. Problem Statement for Estimating the Remaining Useful Life

Large amounts of condition monitoring data are generated during the flight of modern aircraft. For example, about a thousand parameters are continuously monitored during the operation of a Boeing 787 engine [30], which are the basis for estimating its remaining useful life and predictive maintenance.

The objective of predicting the remaining useful life is to estimate the period between the current time and that of an engine failure. The problem of estimating the remaining useful life can be formulated in two possible ways. The first statement is to determine whether there exists a probability of failure within the next n time instants/steps (a multiclass classification problem). The second one is to predict the remaining time to failure, i.e., the number of operating cycles until the engine fails (a regression problem).

The following scenario was considered in [31]. The operability state of a set of engineering system instances (denoted by U) is tracked and stored in multi-sensor data until the end of the remaining useful life. For each system instance $u \in U$, the collected multi-sensor data are a multidimensional time series $X^{(u)} = \left\{x_1^{(u)}, x_2^{(u)}, \ldots, x_L^{(u)}\right\}$, where L is the last life cycle of the system and $x_t \in \mathbb{R}^n$ is the vector of the n sensor readings at a time instant t: $x_t^{(u)} = \left[x_{tj}^{(u)}\right]_{j=1}^{n}$. The set $\left\{X^{(u)} \mid u \in U\right\}$ consists of the sensor readings before a failure occurs. The goal is to construct a nonlinear mapping as follows:

$$f_{\Theta_p} : X^{(u)}(t, l) \to R_t^{(u)},\ t \in \left\{l, l+1, \ldots, L^{(u)}\right\},$$

where Θ_p is the set of parameters determined during model training; $X^{(u)}(t, l)$ is a subsequence of length l for the time series $X^{(u)}$ starting from the time instant $t - l + 1$, i.e.,

$$X^{(u)}(t, l) = \left\{x_{t-l+1}^{(u)}, x_{t-l+2}^{(u)}, \ldots, x_t^{(u)}\right\};$$

$R_t^{(u)}$ is the remaining operating time until failure at the time instant t. The model is built in the autonomous mode (offline). Once the nonlinear mapping model is well-trained, it can be used to predict the remaining useful life for other system instances U^* in real time. For each system $u^* \in U^*$, the predicted remaining useful life is given by

$$\hat{R}_t^{(u^*)} = f_{\Theta_p}\left(x_{t-l+1}^{(u^*)}, x_{t-l+2}^{(u^*)}, \ldots, x_t^{(u^*)}\right),$$

$$t \in \left\{l, l+1, \ldots, L^{(u^*)}\right\}.$$

The trained model can be applied to estimate the remaining useful life of the system under consideration using historical and current sensor data.

Computational experiments are carried out to compare different models and methods and assess their effectiveness. In many cases, such experiments utilize *Commercial Modular Aero-Propulsion System Simulation* (C-MAPSS), the turbofan engine dataset freely provided by NASA [32, 33]. This popular set contains multivariate time data from 21 sensors generated by the Modular Aero-Propulsion System Simulation program. The dataset consists of four subsets, each divided into a training sample (condition monitoring data recorded before a turbofan engine failure) and a test sample (data terminated at a definite point before a complete failure). The goal is to predict the remaining useful life for the test data. The condition monitoring data are multivariate time series that simulate the behavior of aircraft engines. Condition monitoring data are contaminated with noise, and the initial wear state and production variation of turbofan engines are unknown, which complicates the accurate prediction of the remaining useful life [34].

In 2021, a new turbofan engine degradation dataset, N-CMAPSS, was published [35]. Compared to the previous counterpart, N-CMAPSS provides operation-to-failure trajectories for a small fleet of aircraft engines under realistic flight conditions.

To estimate a regression model, a common approach is to use the root-mean-square error

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(e_i^2\right)},$$

where e_i is the difference between the predicted and true values of the remaining useful life. The accuracy of a classification model is the probability that the class will be predicted correctly.

Based on C-MAPSS data, regression and classification approaches with machine learning methods (RF, SVM, and deep learning with LSTM) for estimating the remaining useful life were compared in [36]. For the regression approach, the RMSE values were 19.98 (RF), 20.91 (LSTM), and 20.512 (SVM). Thus, RF is the best method when implementing regression. However, according to the results of the study, classification performs better and faster than regression for this problem. For the classification approach, the accuracy estimates were 98.7% (LSTM), 95.6% (SVM), and 90.3% (RF). Obviously, the classification approach based on LSTM is more accurate and faster than the other methods for calculating the remaining useful life in the predictive maintenance of aircraft engines.

The accuracy of various machine learning and deep learning models for aircraft engine maintenance prediction was investigated in [37]. In particular, deep learning methods (LSTM, Bi-LSTM, RNN, Bi-RNN, and GRU) and conventional machine learning methods (RF, *k*-NN, naive Bayesian classifier, and GB) were used to predict an aircraft engine failure from the C-MAPSS dataset during a predetermined number of cycles. High accuracy values of 97.8%, 97.14%, and 96.42% were achieved with GRU, Bi-LSTM, and LSTM, respectively. Therefore, these models can predict the need for aircraft engine maintenance at an early stage.

Deep learning also provides significant performance improvements compared to traditional methods [38].

1.2 Feature Extraction Using Autoencoders

For aircraft engines, condition monitoring data are complex and multidimensional, so it is necessary to extract high-level features from the data for unsupervised anomaly detection. In recent time, *autoencoders* have been frequently used to extract features from complex and multidimensional unlabeled datasets. An autoencoder consists of two parts: an encoder and a decoder. An encoding function serves to map the input vector $x \in R^n$ into a hidden representation $h \in R^m$:

$$h = f_\theta(x) = S_1(Wx + b),$$

$$S_1(x) = \max(0,\ x),$$

where W is a weight matrix of dimensions $m \times n$; $b \in R^n$ is a bias vector; $S_1(\cdot)$ is the ReLU activation function.

The hidden representation is then mapped into the output vector using the decoding function:

$$z = g_{\theta'}(h) = S_2(W'h + b'),$$

$$S_2(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}},$$

where W' is a weight matrix of dimensions $n \times m$; b' is a bias vector; $S_2(\cdot)$ is the tanh activation function.

The objective function of the model is the sum of all squared errors between the input and output vectors:

$$J(\theta, \theta') = \sum_{x \in V} L(x, z),$$

where L is the squared error and V is a training dataset.

The objective function is minimized using the error backpropagation algorithm to find the optimal parameters $\{\theta, \theta'\} = \{W, b, W', b'\}$.

To build a deep autoencoder, the training dataset is divided into several minipackets, and the parameters are updated by minimizing the loss function for the minipacket:

$$L(x, z) = \frac{1}{K} \sum_{k=1}^{K} \left\| x_k - z_k{}^2 \right\|,$$

where K is the size of the minipacket.

To construct a deep multilayer neural network, the previous hidden layer is used as input data for the next layer. Multidimensional data are converted into low-dimensional ones by training a multilayer neural network with a small central layer to recover multidimensional input vectors. According to [39], autoencoders as a tool for reducing the data dimension perform much better than Principal Component Analysis (PCA). Gradient descent is applied to fine-tune the weights in autoencoder networks. As argued by the authors, dimension reduction using deep autoencoders will be very effective given fast enough computers, large enough datasets, and the initial weights close enough to a good solution.

However, conventional deep autoencoders do not cope well with unbalanced data; at the same time, engine condition monitoring data are extremely unbalanced due to the existence of much more normal operation data compared to abnormal ones and the possible absence of some abnormal operation types. A re-optimized deep autoencoder for gas turbine abnormality detection based on unlabeled operational data was presented in [40]. It involves a mechanism for automatically removing anomalous samples from the unlabeled training dataset and training the autoencoder using only normal samples. As a result, the errors in decoding anomalous samples become more distinguishable from those in decoding normal samples.

The re-optimized autoencoder consists of two conventional deep autoencoders and a clustering algorithm. The first autoencoder is trained on the original dataset, and the trained model is used to compute errors for the input vectors. The anomaly is indicated by the reconstruction error between the input vector and its low-level reconstruction. The obtained errors are split into two classes using the clustering algorithm, with samples with large reconstruction errors treated as anomalous ones. A new training dataset is formed from the cluster of all vectors with small errors. Compared to the original one, the new training dataset contains fewer or even no vectors for anomalous states. A second autoencoder trained to minimize the decoding errors on the new training dataset can detect anomalies better (Fig. 1) [40]. Then, the reconstruction errors learned with the help of the re-optimized autoencoder and the hidden functions from the original samples are together transferred to an isolation forest for unsuper-

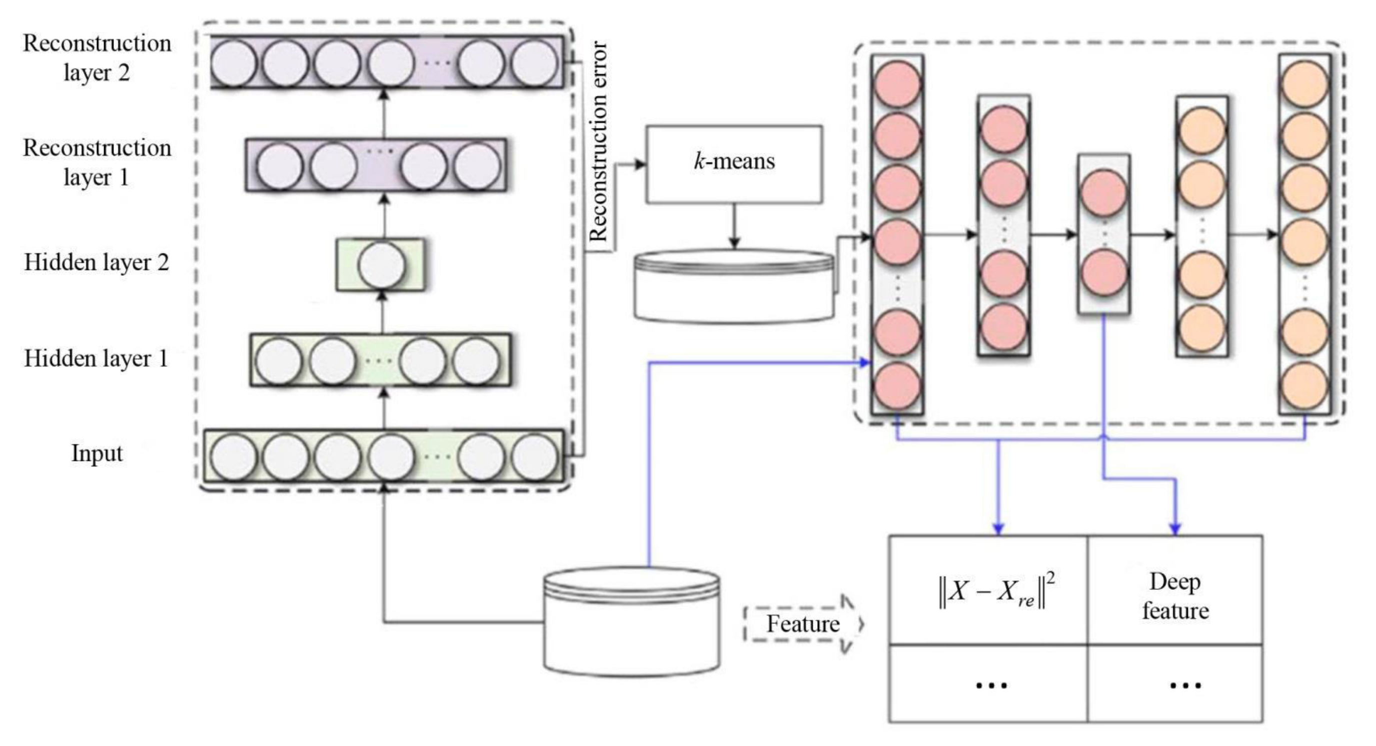

Fig. 1. The re-optimized deep autoencoder.

vised anomaly detection. The authors recommended using samples from multiple engines, as this eliminates well the negative impact of individual engine differences on anomaly detection and effectively addresses the problem of insufficient training due to not enough samples for a single engine.

1.3 Models Based on Convolutional Neural Networks

Convolutional neural networks are widely used in deep learning. The popularity of CNNs is due to their ability to read, process, and extract the most important features of 2D data, which contributes to high performance, especially for image classification. Aircraft engine condition monitoring data are multivariate time series of length M and width N, where M is the number of time steps in the data and N is the number of variables in the multivariate time series. They can be used as input data for convolutional neural networks, see Fig. 2 [28].

When transforming time series data, the 1D convolution kernel has the same width N. The kernel moves top-to-bottom, performing convolutions to the end of the series. The elements of the time series covered at a given time instant (the window) are multiplied by the elements of the convolution kernel, the results are summed up, and a nonlinear activation function is applied to this sum. The resulting value becomes the element of the next (new) filtered series. The kernel then proceeds to create the next value. The max pooling is applied to each filtered vector series. The largest vector value is selected and taken as the input data for the common fully-connected layer. The standard artificial neural network structure usually consists of an input layer, one or more hidden layers, and an output layer. The number of hidden layers and neurons used to reach an optimal solution varies from situation to situation and is chosen by trial and error.

A CNN-based regression approach to estimating the remaining useful life was considered in [41, 42]; convolutional and pooling filters (gates) were applied in the time dimension to the multichannel sensor data for systematic automatic feature learning from raw signals. A multiscale deep CNN was proposed in [43]. It has different convolutional gates of different sizes to extract more detailed features for estimating the remaining useful life. The approach was assessed and compared with other methods (deep neural network, RNN, network with LSTM, and deep CNN) on the C-MAPSS dataset. As noted in [44], according to the simulations carried out for multiclass classification based on available NASA datasets, the time series-to-image transformation with the subsequent application of a convolutional neural network demonstrates acceptable results in predicting the remaining useful life of aircraft engines. The results can be further improved by increasing the amount of data to train the model.

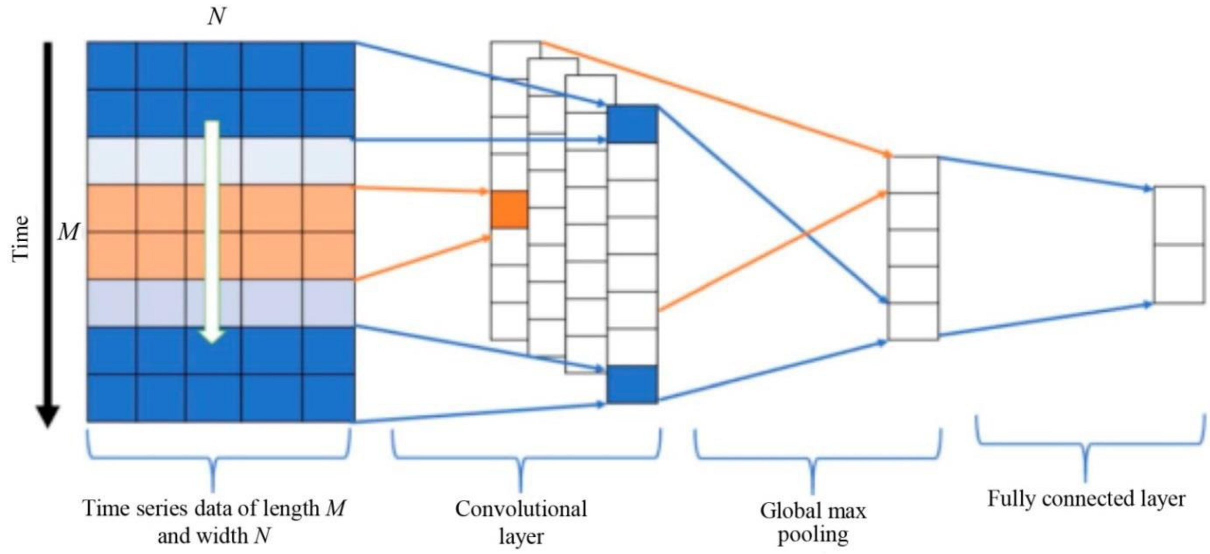

Fig. 2. The convergence network for time series data.

1.4 Models Based on Recurrent Neural Networks

Recurrent neural networks are neural networks containing feedback loops. Such networks are well suited for time series processing. For an input time sequence $x = (x_1, \ldots, x_r)$, an RNN yields a hidden vector sequence $h = (h_1, \ldots, h_r)$ and, in the final result, an output vector sequence $y = (y_1, \ldots, y_r)$. The iterative computation equations have the following form in the time range $t = \overline{1, T}$:

$$h_t = H\left(W_{xh} x_t + W_{hh} h_{t-1} + b_h\right),$$

$$y_t = W_{hy} h_t + b_y,$$

where W are weight matrices; b are bias vectors; H is an activation function (usually, the sigmoid function).

A conventional RNN is a chain of recurrent modules that use only the previous input data. In *Bidirectional Recurrent Neural Networks* (BRNNs) [45], an input data sequence is supplied to two hidden layers (Fig. 3). The bidirectional approach makes it possible to apply both past and future contexts.

An ensemble method of deep BRNNs was proposed to predict the remaining useful life of an aircraft engine [46]. The method was validated using C-MAPSS datasets. According to the experimental results, this method achieves high performance.

When training on long data sequences in a recurrent neural network, the vanishing/exploding gradient problem may arise. In addition, it is not possible to detect long-term sequential dependencies using a recurrent neural network. An important type of RNNs is networks with LSTM and GRU cells: due to their structure, information can be stored for a long time.

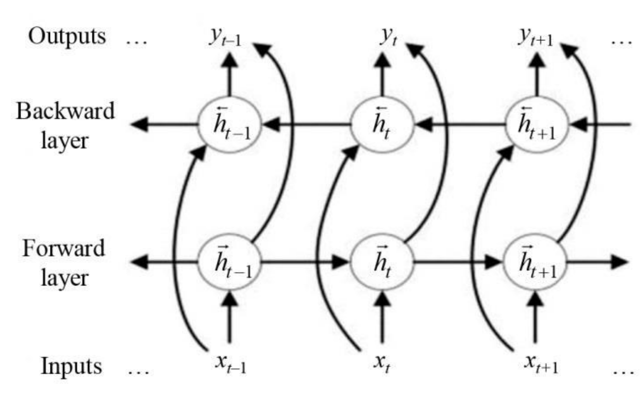

Fig. 3. A bidirectional recurrent neural network.

1.5 LSTM-Based Models for Studying Long-Term Dependencies

The LSTM unit [47] is a specially designed memory cell with a system of gates added to limit the information flow. The gate function is usually a sigmoid function whose output signal ranges from 0 to 1; this value determines the share of information to be skipped. The LSTM structure [48] is shown in Fig. 4.

The gate functions are described by the following equations:

$$i_t = \sigma\left(W_{xi} x_t + W_{hi} h_{t-1} + b_i\right),$$

$$f_t = \sigma\left(W_{xf} x_t + W_{hf} h_{t-1} + b_f\right),$$

$$o_t = \sigma\left(W_{xo} x_t + W_{ho} h_{t-1} + b_o\right),$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh\left(W_{xc} x_t + W_{hc} h_{t-1} + b_c\right),$$

$$h_t = o_t \odot \tanh c_t,$$

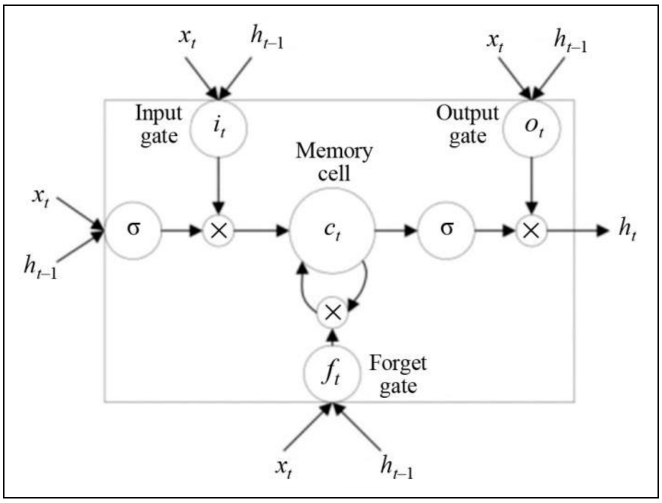

Fig. 4. An LSTM cell.

where i, f and o are the input, forget, and output gates, respectively; c denotes the memory cell; h stands for the hidden vector sequence; σ is the sigmoid activation function; finally, $\odot$ is the elementwise multiplication of vectors. The equations of the three elements have the same structure, but the weight matrices take different values. The input gate i controls the information entering the memory cell c_t. The forget gate f controls the information of the last memory cell c_{t-1} accumulated in the current memory cell c_t. The output gate o affects the information entering the hidden state h_t. The gate system allows avoiding the vanishing/exploding gradient problem.

Owing to deep architectures, the model learns high-level raw input data and finds long-term dependencies in sequences, so they are well suited for predicting the remaining useful life. Many researchers propose their LSTM-based models for aircraft engine failure prediction and, comparing them with earlier approaches, claim that LSTM-based methods improve the prediction of the remaining useful life of aircraft engines and provide better performance [3, 49, 50]. The method presented in [51] combines a 1D convolutional network with a full convolutional layer and a network with LSTM to predict the remaining useful life of turbofan engines. To address the unbalanced data problem, a general fault prediction framework incorporating LSTM-based autoencoder function training methods was described in [52]. The problems related to the effects of noise in complex operations and various abnormal conditions were considered based on a two-channel LSTM neural network model [53]. A model combining a broad learning system for feature extraction and an LSTM for processing time series information was presented in [54], with application to predicting the remaining useful life. For the vanishing gradient problem, a bidirectional supervised recurrent unit with GRU cells was considered in [55]. The method was assessed using data from a real aircraft maintenance system. According to the assessment results, this method is effective in predicting component failures on a predetermined significant period.

1.6 The Attention Mechanism

The input characteristics provided by multiple sensors differently affect system degradation. The prediction results of the remaining useful life have different correlations with the input data at different time steps, and the time correlation may change with the degree of degradation. Thus, among multiple input data, it is necessary to focus on more important information to obtain a satisfactory accuracy of prediction. Guided by this aspect, researchers develop attention mechanisms as an important part of the prediction model to select the most relevant input features and adaptively extract the time correlation.

As shown in Fig. 5 [31], the feature attention mechanism mainly consists of a multilayer perceptron and a softmax layer.

At each time step, each input feature is estimated using a multilayer perceptron by addressing the previous hidden state of the encoder:

$$p_{tj} = \nu_p^T \tanh\left(W_p\left[h_{t-1}^{(E)};\, x^j + b_p\right]\right),$$

where p_{tj} denotes the attention estimate of the jth sensor data at a time instant t; $x^j = \left[x_{1j},\, x_{2j}, \ldots,\, x_{lj}\right]^{\mathrm{T}} \in \mathbb{R}^l$ is the time series of the jth sensor; finally, $h_{t-1}^{(E)}$ is the previous hidden state of the encoder. In addition, m specifies the number of hidden neurons in the encoder; $\nu_p \in \mathbb{R}^l$, $W_p \in \mathbb{R}^{l\times(m+l)}$, and $b_p \in \mathbb{R}^l$ are weight matrices and bias vector to be determined during training.

The attention weight of each input feature can then be found using the softmax layer:

$$\varpi_{tj} = \frac{\exp(p_{tj})}{\sum_{j=1}^{n} \exp(p_{tj})},$$

where ϖ_{tj} is the attention weight of the jth sensor data at a time instant t, which reflects the significance of the jth sensor data. With the attention weights, we can

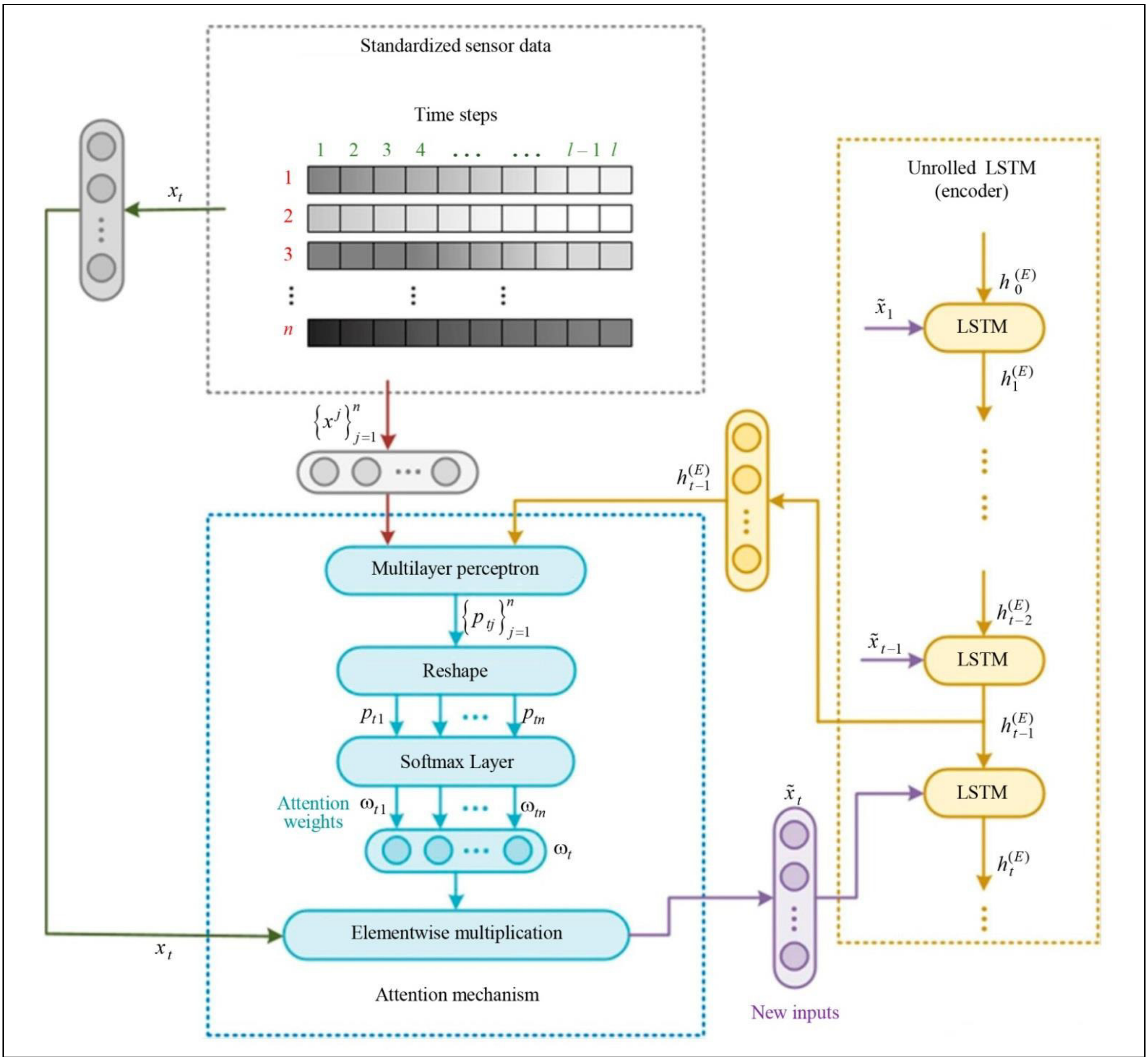

Fig. 5. The feature attention mechanism.

sample the input data based on their significance via the operation

$$\tilde{x}_t = \varpi_t \odot x_t,$$

where $\tilde{x}_t$ corresponds to the newly computed input signal at the time instant t; $\left[\varpi_{tj}\right]_{j=1}^{n} = \left[\varpi_{t1}, \varpi_{t2}, \ldots, \varpi_{tn}\right] \in \mathbb{R}^n$ is the attention weight vector at the time instant t.

A modified LSTM method with an attention mechanism improving the prediction of the remaining useful life of aircraft engines was proposed in [56]. To achieve more accurate prediction results, a convolutional network was used with an attention mechanism to collect long-term time series information [57]. An architecture based on a convolutional neural network and a dual attention mechanism was applied to predict the remaining useful life of an aircraft engine by assigning larger weights to more significant features at critical time steps [24].

A deep learning architecture called the distance self-attention network was described in [58]. This architecture combines historical information and real-time data and incorporates a distance function to improve the feature extraction capability; data fusion is based on a recurrent neural network. The effectiveness of the method for estimating the remaining useful life was verified using C-MAPSS data. According to the experimental results, the method outperforms common methods based on a convolutional neural network or a network with LSTM: the RMSE value decreased by 7.3–25.3%.

1.7 Models with the Transformer-Based Architecture

Many models presented above have demonstrated good performance with C-MAPSS simulation data. However, in new research works, the transformer-based architecture is used instead of convolutional and recurrent neural networks to estimate the remaining useful life of an aircraft engine under real rather than simulated flight conditions. It was pioneered in 2017; for details, see [59].

This neural network architecture utilizes a multi-head self-attention mechanism with the dynamic estimation of the significance of different elements in a sequence, being well suited for processing data sequences. The main advantage of transformer-based models lies in their ability to handle long-term dependencies in sequences, overcoming the vanishing gradient problem inherent in recurrent networks. In addition, this architecture makes it possible to process input sequences in parallel.

A transformer-based architecture model for estimating the remaining useful life of turbofan engines was proposed in [60]. In this model, a multi-head self-attention mechanism serves to extract functions from variable-length input data and capture the features of each mode under real flight conditions. The transformer-based dual-aspect self-attention [61, 62] was designed for a detailed understanding of both temporal dynamics and the contribution of individual sensors to implement a more complete capability of predicting the remaining useful life of a turbojet engine. A two-stage hierarchical transformer structure described in [63] fixes both the time and sensor variables for prediction and utilizes a hierarchical encoder–decoder structure to capture time information at different time scales. The reliability of predicting the remaining useful life of turbofan was considered in [64] by quantifying the uncertainties due to the model error and data randomness.

1.8 Predicting the Remaining Useful Life of Aircraft Engines: Comparison of Methods

To improve the prediction accuracy, hybrid models combining different architectures are proposed to deal with irregular patterns and trends caused by the nonuniform data distribution.

Several methods for predicting the remaining useful life of aircraft engines were compared in [63, 65]. The table below presents the assessments of the following methods:

- the deep convolutional neural network (CNN) [41],
- the long short-term memory (LSTM) network [66],
- the bidirectional network with long short-term memory (BiLSTM) [48],
- the multi-head architecture that utilizes parallel CNN branches serially with LSTM (*Multi-head* CNN+LSTM) [67],
- the *Gated Convolutional Transformer* (GCT) [68],
- a model that extracts data features based on a broad learning system and uses LSTM for time series processing (B-LSTM) [54],
- the *Dual-Aspect Self-attention Transformer* (DAST) [61],
- the transformer based on the bi-directional LSTM autoencoder (BiLSTM-DAE Transformer) [65], and
- the *two-stage attention-based hierarchical Transformer* (STAR) [63].

The effectiveness of the methods was assessed using two metrics: RMSE and Score.

The Score metric imposes a smaller penalty for proactive maintenance planning if $y_i < y_i$. In the case $y_i > y_i$, a higher penalty is applied due to the more serious consequences of too late maintenance. That is,

$$Score = \begin{cases} \sum_{i=1}^{N} e^{-\left(\frac{y_i - y_i}{13}\right)} - 1, \; y_i - y_i < 0, \\ \sum_{i=1}^{N} e^{-\left(\frac{y_i - y_i}{10}\right)} - 1, \; y_i - y_i \geq 0. \end{cases}$$

where y_i and y_i are the predicted and true RUL, respectively, and N specifies the number of sample sequences in the dataset.

The publicly available C-MAPSS turbofan engine dataset containing four subsets of data (FD001, FD002, FD003, and FD004) was used for model comparison and assessment. The data in each subgroup are intended to estimate the model's performance under different conditions. The operating conditions and fault modes generate additional complexity in the dataset, making it a suitable benchmark for assessing predictive models.

Comparison of models for predicting the remaining useful life of aircraft engines

Method	The values of metrics for different data subgroups							
	FD001		FD002		FD003		FD004	
	RMSE	Score	RMSE	Score	RMSE	Score	RMSE	Score
CNN (2016)	18.45	1290	30.29	13 600	19.82	1600	29.16	7890
LSTM (2017)	16.14	338	24.49	4450	16.18	852	28.17	5550
BiLSTM (2018)	13.65	295	23.18	4130	13.74	317	24.86	5430
Multi-head CNN+LSTM (2020)	12.19	259	19.93	4350	12.85	343	22.89	4340
GCT (2021)	11.27		22.81		11.42		24.86	
B-LSTM (2022)	12.45	279	15.36	4250	13.37	356	16.24	5220
DAST (2022)	11.43	203	15.25	924.96	11.32	154	18.36	1490
BiLSTM-DAE Transformer (2023)	10.98	186	16.12	2937	11.14	252	18.15	3840
STAR (2024)	10.61	169	13.47	784	10.71	202	15.87	1449

2. AIRCRAFT ENGINE MAINTENANCE PLANNING

In Section 1, we have reviewed methods for predicting the remaining useful life of aircraft engines. The challenge arises to integrate such prediction procedures into maintenance planning. It has been addressed in several studies.

Reinforcement learning is widely applied to solve various problems, including optimal maintenance prediction in various forms, ranging from early fault diagnosis to direct suggestion of maintenance actions [69]. A reinforcement learning approach to the long-term aircraft maintenance optimization problem was proposed in [70]. Within this approach, information about the aircraft's future flight, repair cost, forecasts, condition management, etc. is utilized to make sequential maintenance decisions in real time. The integration of the reinforcement learning model for human-artificial intelligence cooperation in maintenance planning and the visualization of condition-based maintenance indicators were proposed in [71]. Reinforcement learning was applied for maintenance planning and scheduling in [72]. The approach presented therein consists of a static long-term planning algorithm and an adaptive replanning algorithm based on optimal maintenance decision-making in case of unforeseen events. A method for predicting unplanned aircraft maintenance tasks by applying deep reinforcement learning techniques and log data from a central aircraft maintenance system was described in [73].

A dynamic fleet maintenance system with periodically updated predictions of the remaining useful life of components was proposed in [74]. The planning of maintenance tasks is initiated soon after triggering an alarm signal. Alarm signals are based on changes in forecasts over time. Tasks are planned using a sliding horizon approach with time windows. In each time window, planned maintenance intervals are determined by integer linear programming. The parameters of the maintenance structure are obtained via a genetic algorithm.

This maintenance structure was illustrated for a fleet of 20 aircraft from the C-MAPSS dataset, with two turbofan engines for each aircraft. The remaining useful life of the turbofan engines was predicted using a convolutional neural network and updated every day. According to the results, due to imperfect prediction, engine failures still occur due to a limited number of maintenance locations or a limited number of maintenance tasks that can be performed in a limited amount of time. Compared to the perfect prediction case, the maintenance costs are higher by 24.4%.

In prediction, it is important to consider the uncertainty inherent in models and data. Therefore, a meaningful prediction of the remaining useful life should at least be accompanied by confidence intervals and, even better, described through probability distributions (if possible) or fuzzy representations [75].

An approach to integrate the probability distribution of the remaining useful life of aircraft engines into optimal engine replacement planning was proposed in [76]. Within this approach, probabilistic forecasts are calculated based on convolutional neural networks and Monte Carlo simulations [77]. The resulting probabilistic forecasts are used to develop a deep reinforcement learning method for aircraft engine maintenance planning. The goal is to optimally schedule engine replacement to avoid failures and minimize the lost engine life [76].

In particular, the maintenance schedule is regularly updated after D flight cycles. At decision step t, the probability that the remaining useful life of the engine does not exceed k cycles, $p_{k,t}$, is estimated given sensor measurements x_t:

$$p_{k,t} = P\left(R_t \le k | x_t\right) \text{ for } k \in \{1, \ldots, D\}.$$

An engine fails at cycle k if $(k-1) < \rho_t \le k$, where ρ_t is its true remaining useful life and R_t is the estimate of ρ_t (the remaining useful life of the engine at the beginning of step t).

The state s_t is determined by the distribution $p_{k,t}$ for the next D flight cycles:

$$s_t = \left[p_{1,t}, \ldots, p_{D,t}\right].$$

Based on the state s_t, the agent selects an appropriate action:

$$a_t = \begin{cases} k, \ 0 < k \le D \ \text{(replace the engine in cycle } k\text{)} \\ K, \quad K > D \ \text{(do nothing).} \end{cases}$$

If the agent decides not to replace the engine, the sensor measurements x_t and the distribution $p_{k,t}$ are updated at the next step $t + 1$. Therefore, all decisions made rest on the latest forecasts.

At a step t, the reward r_t depends on the values of a_t and ρ_t:

$$r_t = \begin{cases} -c_{\text{sch}}(k) & \text{if}\left(k-1 < a_t \le k\right) \& (\rho_t > k) \\ -c_{\text{sch}} & \text{if}\left(k-1 < a_t \le k\right) \& (\rho_t \le k) \\ -c_{\text{uns}} & \text{if}\left(a_t > D\right) \& \left(\rho_t \le D\right) \\ 0 & \text{if } \left(a_t > D\right) \& (\rho_t > D), \end{cases}$$

where $c_{\text{sch}}(k) = c_0 - c_1 k$ is the cost of planned (scheduled) engine replacement in cycle k; $c_0 > 0$ is the fixed cost of replacement; $c_1 > 0$ is the penalty for early replacement; finally, $c_{\text{uns}} > c_0$ is the cost of unscheduled replacement.

The agent chooses an action a_t in a state s_t based on a strategy $\pi(a_t | s_t)$ (the probability of choosing the action a_t in the state s_t). The optimal strategy π^* maximizes the expected reward:

$$J(\pi) = \sum_t \mathbb{E}_{(s_t, a_t) \sim \rho_\pi} [\gamma^t r_t (s_t, a_t)],$$

where γ is the discount factor and $\rho_\pi(s_t, a_t)$ is the distribution of the state–action trajectories under the strategy π.

A soft actor-critic algorithm [78] is used to train the agent. Compared to the actor-critic algorithm, this algorithm involves stochastic policies and maximizes the soft objective for learning new policies. It determines the optimal engine replacement time considering different distribution trends of the remaining useful life. This approach will reduce maintenance costs and the number of unscheduled events compared to other maintenance strategies.

CONCLUSIONS

The transition to predictive maintenance based on data from onboard condition monitoring sensors of aircraft engines and the prediction of their remaining useful life will improve operational safety and reduce aircraft maintenance costs. Considering the nature of the time series of aircraft engine monitoring data and the results of this literature survey, we conclude that the trend of estimating the remaining useful life and predicting aircraft engine failures is shifting from conventional machine learning methods to deep learning neural networks. Currently, many different deep learning methods and algorithms of neural networks are proposed for the fault diagnosis and remaining useful life prediction of aircraft engines, in particular, those with autoencoders to detect rare failures, convolutional or recurrent neural networks with LSTM or GRU cells to predict the occurrence of the next failure, and transformer-based architectures with attention mechanisms. In recent years, there have been attempts to provide interpretability while maintaining prediction accuracy based on models such as SHAP (*SHapely Additive exPlanations*) and LIME.

Note that the authors mostly use the publicly available C-MAPSS turbofan engine simulation dataset to analyze and compare the effectiveness of their methods and algorithms. However, there are significant differences between simulation data and the data obtained under practical flight conditions. Further research is needed to predict the remaining useful life based on real aircraft engine condition datasets.

The goal of predicting the remaining useful life of aircraft engines is to anticipate failures and optimize the performance of maintenance tasks. One of the important tasks of predictive maintenance is to integrate the resulting predictions of the remaining useful life of aircraft engines into maintenance planning. In this context, attention should be paid to aircraft engine maintenance planning based on deep reinforcement learning with probabilistic forecasts.

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