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PERFORMANCE EVALUATION OF DATA-DRIVEN PROGNOSTIC BASED ON RVM-SBI TECHNIQUE

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Abstract

The Prognostic and Health Management (PHM) becomes a research topic in its own right and tends to be more and more visible within the scientific community such as in Nasa Society, which has provided datasets for experiments. The purpose of this paper is to evaluate the performance of a data-driven prognostic technique used for predicting Remaining Useful Life (RUL). The methodological support of the proposed approach integrates all data-driven prognostic sequential steps merged in offline and online part. To design the predictive degradation model on the offline part, the Relevance Vector Machine (RVM) algorithm was applied. On the online part, prediction of the RUL is based on the Similarity-Based Interpolation (SBI) algorithm. The different steps of the methodology are described and their implementation undertaken through a case study involving the degradation dataset of turbofan engines from the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS). Finally, results are compared with other techniques applied on the same dataset.

Keywords: Data-driven prognostic, prognostic and health management, relevance vector machine, remaining useful life, similarity-based interpolation.

1. Introduction and Literature Review

In order to maintain systems in operating condition and ensure their reliability while guaranteeing their high performance, maintenance strategies have evolved from corrective and/or traditionally preventive to predictive, and more specifically to Prognostic and Health Management (PHM). In the literature, many classifications of prognostic have been proposed, the first ones being Lebold and Thurston (2001) and Byington (2001). This classification has been adopted in many works and is classified in pyramidal form into three approaches according to their complexity of labor, cost, and precision of obtained results and applicability of approaches. Fig. 1 summarizes different prognostic approaches.

This paper focuses on data-driven prognostic approach for RUL prediction of industrial systems. This approach is suitable for any type of instrumented application in which the knowledge of degradation mechanisms is directly included in the data. No knowledge of analytical degradation models is thus required. This approach is based on the following observation: measurements are often the strongest and most reliable source of information for understanding degradation phenomena. This type of approach aims to learn through the degradation phenomenon and to capture the subtle relationships between data, even if these relationships are unknown or difficult to describe. They are, therefore, based on the use of monitoring data from sensors called Physics Health Index (PHI) which are processed in order to extract characteristics reflecting the behavior of the system and its degradation. The use of PHI has become increasingly difficult with its multitude of heterogeneous sensory signals. To overcome this complexity of PHI, Synthesized Health Index (SHI) construction is an imperative as developed in certain papers (Khelif et al. 2014, Malhotra et al. 2016, Wang et al. 2012, Xi et al. 2014).

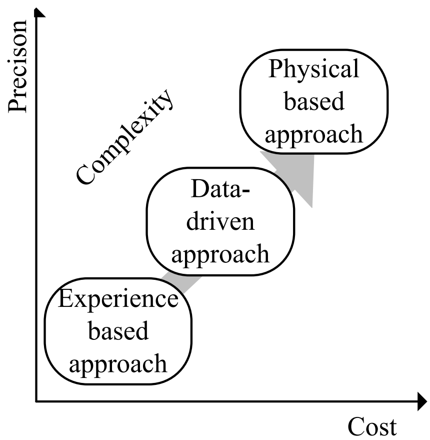

Fig. 1. Prognostic approaches classification.

Developing a good predictive degradation model is of major concern in a data-driven prognostic approach for RUL prediction of mechanical and industrial systems. Several techniques are spotted in different interesting relevant applications. Support Vector Machine (SVM) is a technique based on statistical learning theory proposed by Vapnik (1997). Soualhi (2014) used the SVM method to create a bearings degradation model. Ordóñez (2019) used the results of the Auto-Regressive Integrate Moving Average (ARIMA) method, which estimates the values of the predictor variables to create a model with the SVM method of aircraft turbofan engine. Benkedjouh (2013) and Saidi (2015) used the Support Vector Regression (SVR) to estimate the RUL of bearings in a mechanical application. The SVR is a regression algorithm that allows using continuous values, instead of SVM classification. Rabiei (2016) also used the SVR method to define a correlation between input variables. Their aim was to estimate damage and to predict the appearance of cracks in a metal alloy subject to fatigue crack. Benkedjouh (2015) applied this method to estimate the wear increase in a high-speed milling machine and predict the RUL. Khelif (2017) designed a health index and support vector regression to build a turbofan engine model. Relevance Vector Machine (RVM): is a machine learning technique that uses Bayesian inference to obtain parsimonious solutions for regression. The RVM has an identical functional form to the support vector machine. Tzikas (2006) and Saha and Goebel (2008) applied the RVM method to design the predictive degradation model of battery data, and Wang (2012) used it to estimate engine RUL with PHM’08 NASA challenge dataset. Di Maio (2012) estimated the RUL of partially degraded thrust ball bearings by combination of the exponential regression and RVM. Hu and Tse (2013) proposed an RVM-based model to predict the RUL of pump impellers. Voisin

(2013) used this method to create a predictive model based on records of similar units of a fleet of heterogeneous units. Aye and Heyns (2017) proposed the Gaussian Process Regression (GPR) to estimate the RUL of slow speed Bearings. Goebel (2008) and Saha (2010) also applied this method for RUL prediction of batteries. Trappey (2014) applied logistic regression based on the Weibull distribution to estimate lifespan of a power transformer. Zheng (2017) and Elsheikh (2019) proposed Long-Short Term Memory (LSTM) approaches to create a LSTM degradation model using C-MAPSS dataset. Jayasinghe (2018) also used these data to build the model by applying the Temporal Conventional Memory Network. Babu (2016) applied a Convolutional Neural network (CNN) to estimate the RUL of turbofan engine. Li (2018) proposed Deep Convolution Neural Networks (DCNN) and Li (2020) also proposed Multi-Scale Deep Convolutional Neural Network (MS-DCNN) using C-MAPSS dataset. Lim (2016) used the Multi-Layer Perceptron (MLP) method and Trinh & Kwon (2018) applied neural networks using the C-MAPSS dataset. Ghorbani and Salahshoor (2020) used data-level and feature-level fusion approaches to characterize the degradation process of turbofan engine system.

The contribution of this paper is to develop a data-driven prognostic algorithm by proposing a methodological support based on the RVM-SBI techniques. The aim of the work is to predict Remaining Useful Life of turbofan engines and to evaluate the used algorithms performance using adequate metrics. The obtained results are compared with three studies using the same dataset, but applying different data-driven prognostic techniques.

The paper is organized as follows: Section 2 describes the data-driven prognostic sequential steps constituting the methodological support. Then, Section 3 is devoted to implementing all these steps through industrial turbofan engine data treatment using C-MAPSS dataset. In Section 4, calculated performance metrics of RVM-SBI algorithm used are compared with those of TCMN, Deep LSTM, CNN, MLP, SVR, and RVR algorithms, respectively Temporal Convolutional Memory Networks, Deep Long Short-Term Memory, Conventional Neural Network, Multi-Layer Perceptron, Support Vector Regression, and Relevance Vector Regression. Finally, after discussing of these results, a conclusion ends this article.

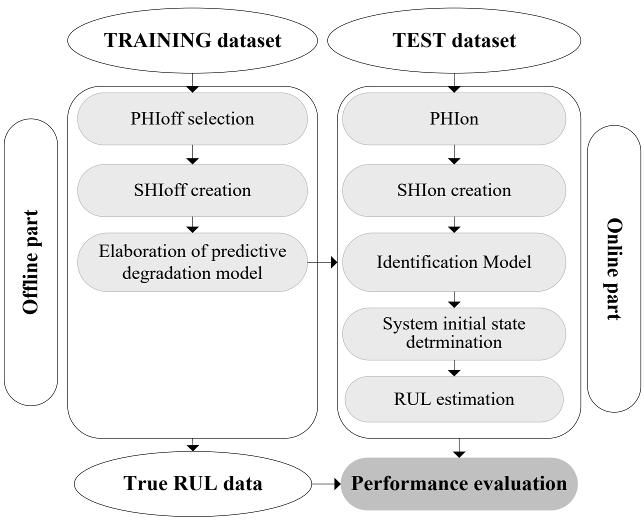

Fig. 2. Methodological support.

2. Methodological Support

Data-driven prognostic relies on the exploitation of training and test datasets to predict the RUL. The proposed methodological support is shown in Fig. 2 where RUL of a turbofan engine from C-MAPSS is used to evaluate the results.

2.1 Generation of the Synthesized Health Index (SHI)

Several methods can be used within data-driven prognostic to build the SHI and manage different types of signals, such as continuous, discrete or binary sensory data. The linear data transformation method is adapted continuously to obtain sensory signals, as in Huang et al. 2015 and Wang 2012.

Suppose that there are two groups of multi-dimensional sensory data representing the system in faulty and healthy condition; the matrix F of $(M_0 \times N)$ and the matrix H of $(M_1 \times N)$ where M_0 and M_1 are respectively the numbers of data for the system in faulty and healthy state and N is the dimension of each given set. With these two matrices, a transformation matrix T (N × 1) can be obtained to transform the multi-dimensional sensory signal into a one-dimensional SHI:

$$T = (Q^T Q)^{-1} Q^T S_{off} \tag{1}$$

Where $Q = [F; H]$, $S_{off} = [S_0, S_1]$, S_0 is a null vector $(1 \times M_0)$ and S_1 is a unit vector $(1 \times M_1)$. This transformation matrix T can transform a set of sensory signals at time t from offline learning, Q_{off} or from the online prediction process Q_{on}, into respectively normalized offline and online synthetized health index:

$$SHI_{off} = Q_{off}.T \text{ or } SHI_{on} = Q_{on}.T \tag{2}$$

The SHI varies between 0 and 1. It contains health signatures extracted from the multi-dimensional sensory signals, which make it possible to construct a predictive degradation model in the offline learning process.

2.2 Elaboration of Predictive Degradation Model

Sparse Bayesian Learning (SBL) is used to design a predictive degradation model of a knowledge-based system, such as the evolution of the degradation model of the studied components. The SBL is a generalized linear model in Bayesian form. It shares the same functional form as the RVM. The conceptual dispersion is obtained by means of a Bayesian treatment in which a prior distribution is set up above the weightings controlled by a set of hyperparameters.

Compared to an SVM (see Li et al. 2020), the non-zero RVM weights represent more prototypical class examples, called relevance vectors. This formed RVM uses far fewer basic functions than the corresponding SVM and generally shows higher test performance.

The unknown value of the real health index function, namely $f(t)$, must be predicted at an arbitrary point t with a set of SHI values, $h_1, \ldots, h_N$, measured at points created at learning $t = \{t_1, \ldots, t_N\}$.

$$h(t) = f(t) + \varepsilon(t) \tag{3}$$

Where ε (t) is the measurement of noise. The RVM, (see Williams & Rasmussen 2006), is a special case of a sparse linear model:

$$h(t) = \sum_{i=1}^{N} \omega_i \Phi(t, t_i) + \varepsilon(t) \tag{4}$$

Where $\omega = \{\omega_1 \ldots \omega_N\}$, the weight of vector functions is formed by the kernel functions $\Phi(t, t_i)$ centered at the learning points $t = \{t_1, \ldots, t_N\}$. The sparse property allows the automatic selection of a suitable kernel at each location by the size of all irrelevant kernels.

2.3 Identification Model

The model identification step is adapted to each online health state with the suitable predictive degradation model and carried out with Root Mean Square Error (RMSE) method. In the beginning, ε_i is calculated by minimizing the RMSE between the online $SHI_{on}(t_j)$ and each point of predictive models throughout the time axis $h_i(j)$, see equation (6). Each online unit then identifies its appropriate model where ε_i attains its smallest value, see equation (5). For an online turbofan engine, the Identification Model (IM) is given by:

$$IM = \arg\min(\varepsilon_i) \tag{5}$$

with

$$\varepsilon_i = min \sqrt{\frac{1}{L_{on}} \sum_{j=1}^{L_{on}} \left(SHI_{on}(t_j) - h_i(t_j) \right)^2} \tag{6}$$

where L_{on} is the online lifetime.

2.4 System Initial State Determination

Degradation time initialization T_0 is a very important point to specify the predictive RUL value using SHI_{on}.

The following equation (7) determines the initial cycle T_0 with the test dataset in which the root mean square error between SHI_{on} and its appropriate model (h_{IM}) reaches a minimum value throughout the time axis in the offline model.

$$T_0 = \arg\min \sqrt{\frac{1}{L_{on}} \sum_{j=1}^{L_{on}} \left(SHI_{on}(t_j) - h_{IM}(T_0 - t_j) \right)^2} \tag{7}$$

The projected RUL_p of the online process according to $h_{IM}(t_j)$ can be calculated by:

$$RUL_p = L_{off} - L_{on} - T_0 \tag{8}$$

Where L_{off} is the offline lifetime.

2.5 RUL Estimation

In the last step consisting of the prediction of the RUL, this study proposes the Similarity-Based Interpolation (SBI) technique, which is the preferred technique at this stage, (see Wang et al. 2008, Wang et al. 2012, Wang et al. 2013).

This similarity is assessed by a measure of distance between the predictive degradation model h and SHI_{on}. This difference gives the similarity weight W, which can be expressed as sum square error:

$$W_i = \left[\sum_{j=1}^{N} \left(SHI_{on_i}\left(t_j\right) - h\left(T_0 + t_j\right) \right)^2 \right]^{-1} \tag{9}$$

The combination of the RUL depends on the match of the online data with the predictive model. Its weight is determined by the system correspondence:

$$RUL = \frac{1}{W} \sum_{i=1}^{K} (W_i RUL_{p_i}) \tag{10}$$

while

$$W = \sum_{i=1}^{K} W_i \tag{11}$$

2.6 Performance Metrics

The main performance metrics are:

Score: It is the asymmetric function used by many researchers (see Saxena et al. 2008a) to evaluate their algorithm. Interval I= [-10, +13] is a range of acceptability defined to measure the estimates quality.

$$S = \begin{cases} e^{-\left(\frac{d_i}{13}\right)} - 1; d_i < 0 \\ e^{-\left(\frac{d_i}{10}\right)} - 1; d_i \geq 0 \end{cases} \; ; \; S = \frac{1}{N} \sum_{i=1}^{N} S_i \tag{12}$$

Where $d_i = estimatRUL_i - true\ RUL_i$, N is the unit number.

RMSE (root mean square error):

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} d_i^{\,2}} \tag{13}$$

Exactitude: Measures the proximity of the predicted failure date to the current failure date. The calculation on this metric represents a critical point in the prognostic process. The exponential function is used here to give a monotonically decreasing smooth curve. The exactitude is great, close to 1 when the expected value is the same as the current value and decreases when the expected value deviates from the current value.

$$E = \frac{1}{N} \sum_{i=1}^{N} e^{\left| \frac{d_i}{trueRUL_i} \right|} \tag{14}$$

3. Case Study – Turbofan Engines RUL Prediction

3.1 C-MAPSS Dataset

A turbofan engine degradation simulation dataset was performed using NASA Commercial Modular Aero- Propulsion System Simulation (C-MAPSS), (see Saxena et al. 2008b). This dataset is subdivided into four subsets that have been simulated under different operating conditions. Each data subset contains a learning file, a test file, and a real RUL file detailed in

Table 1. Both train and test data for each cycle per engine include turbofan engine identification, cycle index, three values for an operational context, and twenty-one sensor measurement values.

For every sample, the turbofan engine operates normally, but it stops immediately when a fault occurs. In the test dataset, the cycle index ends before the system fails. The aim of these collected data is to estimate the RUL and evaluate the accuracy of our prediction by using different metrics.

Dataset	FD_001	FD_002	FD_003	FD_004
Train data	100	260	100	249
Test data	100	259	100	248
Operating conditions	1	6	1	6

Table 1. C-MAPSS dataset.

In this study, our interest lies in the subset data group FD_001. Data file "train FD001.txt" is used for the offline part and "test FD001.txt" is used for the online part. Each data file contains 100 turbofan engines, the purpose of which is to predict the number of operational cycles remaining before the test set fails. The true RUL values for the test data are given in the data file "RUL FD001.txt".

3.2 Result and Interpretation

3.2.1 Offline Part

Step 1

PHI_{off} selection is an important step among the twenty-one sensor signals of the training data, seven of which do not contain any degradation information, see Fig. 3-a. Fig. 3 shows various degradations of the sensors on all turbofan engines. Among 14 signals, only five (T24, T30, T50, Ps30, and BPR) have the same trend, see Fig. 3-b, c, d, e, f, and were selected to best characterize the state of the turbofan engine. The remaining 9 sensors show non-similar degradation information like sensor P30 and NRc, see Fig. 3-g and h.

To take into account the different initial conditions, an adjusted cycle index is calculated as $\mathrm{C_{adj}} = \mathrm{Co} - \mathrm{C_f}$, where Co and $\mathrm{C_f}$ are respectively the operating cycle and faulty cycle of the engine. The cycle number 0 indicates a turbofan engine failure where a negative cycle number corresponds to an operating cycle before the failure. By defining the failure of the reference turbofan engine, the predictive degradation model of the different offline learning turbofan engines with initial system state and degradation paths can be plainly displayed and used easily.

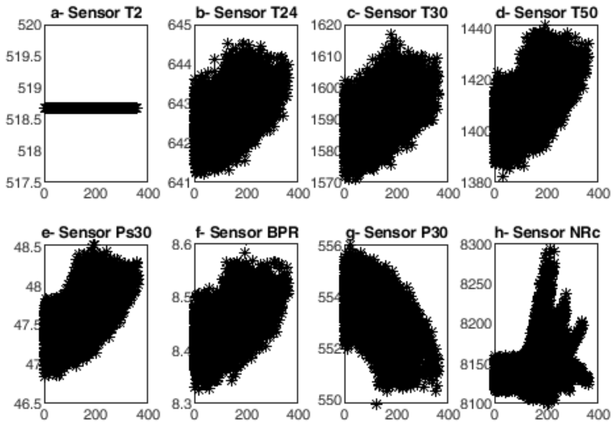

Fig. 3. Sensor selection.

Step 2

In next step, the SHI_{off} construction, as shown in Fig. 4, displays the degradation state of the turbofan engine, from the five sensor signals selected above using the T transformation matrix, see equation (15). The transformation matrices T must be defined according to equation (1) with both matrices Q_0 and Q_1.

In this case study, Q_0 was designed with sensor data in engine failure state in which the adjusted cycle index is between -4 and 0. By the same method, Q_1 was calculated with sensor data in the healthy state in which the adjusted cycle index is less than -300. The transformation matrix T (5×1), in which each row is a transformation vector for the corresponding operating regime points, is shown in equation (15).

$$T = \begin{pmatrix} 0.1095 \\ -0.0065 \\ -0.0134 \\ -0.5265 \\ -1.8256 \end{pmatrix} \tag{15}$$

Fig. 4 represents the evolution of SHI_{off} obtained from the training data set of 3 turbofan engines. The evolution of this point cloud logically decreases from value 1 (healthy) toward the value 0 (faulty), with different lifetime. Engine 1 presents the longest lifetime and follows turbofan engines 2 and 8.

Step 3

Now, this step presents the elaboration of the predictive degradation model. Fig. 5 represents the case of turbofan engine 1. The SBL/RVM technique with Gaussian basic function is used with a few significant relevance vector (RVs). It constitutes a novel approach in relation to this database. This technique is detailed in section 2.2.

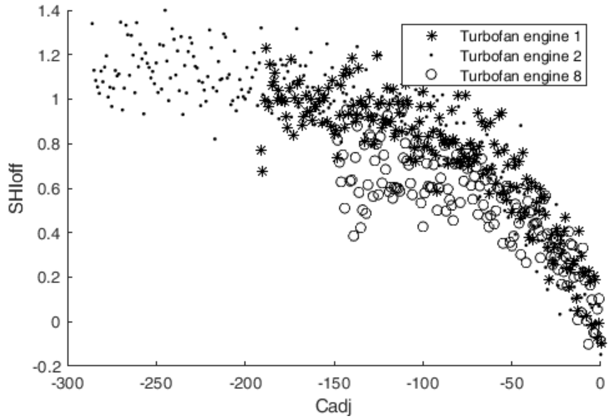

Fig. 4. SHI creation.

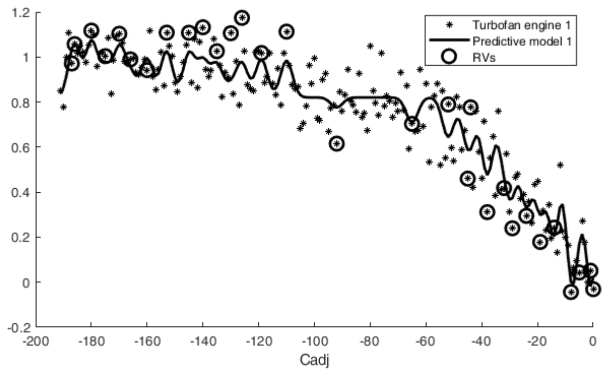

Fig. 5. Predictive degradation model.

3.2.2 Online part

Step 1 and 2

In the online process, the test_FD001 dataset containing 100 online turbofan engines is used. Firstly, and for each engine, the same sensor as selected in the offline part was chosen in this step. Secondly, the PHI_{on} data are used to create the necessary SHI_{on} for the following tasks with the same transformation matrices given in equation (15).

Step 3

Identification of an adequate model for each online unit is a great importance in the RUL estimation. Fig. 6 represents an example of the best degradation model of online unit 1, by calculating RMSE between SHI_{on} and each point of the 100 models using equations (5) and (6): predictive degradation model of turbofan engine 57 is identified as an adequate model of online unit 1 compared to models 8 and 60.

Step 4

Based on equation (8), the initial degradation time T_0 for each turbofan engine is determined by reducing the sum-squared error between SHI_{on} and $h(t_j)$. Fig. 7 illustrates the process to determine the initial degradation time T_0 of engine 1 as well as its RUL_p such that the points represent its SHI_{on} 1 and the curve its predictive degradation model 57. The projected RUL_p of each online engine, using equation (9), is obtained. The replication of this process has provided 100 projected RUL_p on the 100 predictive degradation models.

Step 5

Finally, the SBI technique is employed to determine the similarity weights W_i. In this case, 10 great weights were used to predict the RUL of each turbofan engine using respectively equations (11) and (12).

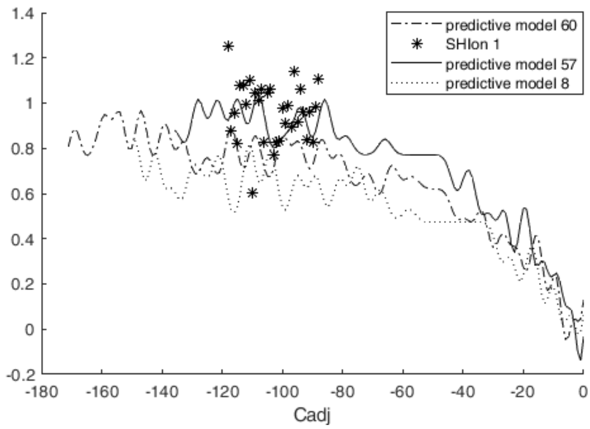

Fig. 6. Identification model.

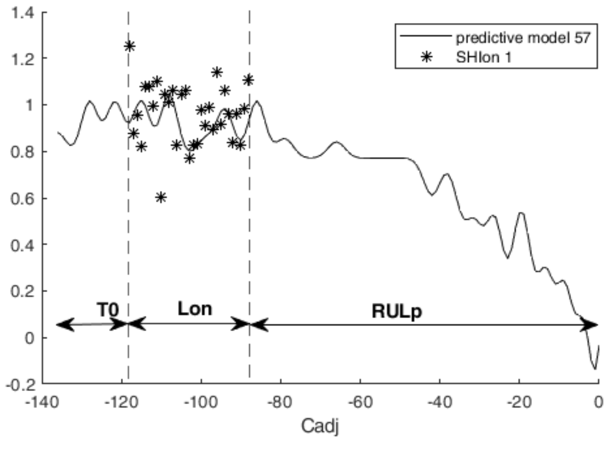

Fig. 7. System initial state determination.

4. Performance Evaluation

In order to evaluate the results obtained in Section 3, the performance metrics using RUL_FD001 files were calculated. These files contain 100 values of the true RUL coupled to equations (12), (13) and (14). As I= [-10, +13] is the range of acceptability, already defined in Section 2.6. The obtained result imply that the prognostic is correct with a score 7.29, root mean square error 19.74 and an accuracy rate of 78% (see Table 2).

Performance metric	Score	RMSE	Exactitude
FD_001	7.29	19.74	0.78

Table 2. Performance evaluation.

In order to verify the accuracy of the algorithm proposed, the results are compared with those obtained in the references (Babu et al. 2016; Jayasinghe et al. 2018; Zheng et al. 2017). They respectively used Temporal Convolutional Memory Networks (TCMN), Deep Long Short-Term Memory (Deep LSTM), Conventional Neural Network (CNN), Multi-Layer Perceptron (MLP), Support Vector Regression (SVR), and Relevance Vector Regression (RVR), see Table 3.

In comparison, the results obtained in this paper with a score of 7.29 are more accurate than those provided by Jayasinghe (2018) and Babu (2016) with scores of 12.2, 12.86, 178, 13.81, and 15.02, while the result of Zheng (2017) presents the best score.

Reference	Method	Score
Jayasinghe et al. 2018	TCMN	12.2
Zheng et al. 2017	Deep LSTM	3.38
Babu et al. 2016	CNN	12.86
	MLP	178
	SVR	13.81
	RVR	15.02
Proposed technique	RVM-SBI	7.29

Table 3. Comparison of score results.

5. Conclusion

The data-driven prognostic algorithm based on the association of artificial intelligence and similarity-based interpolation methods developed in this paper can be successfully used to predict Remaining Useful Life (RUL) of turbofan engines. The methodological support of the proposed approach integrates all data-driven prognostic sequential steps merged into two distinct parts, offline and online part. The offline process, to design the predictive degradation model, is based on the Relevance Vector Machine (RVM) algorithm, while the online process, to predict the RUL, is based on the Similarity-Based Interpolation (SBI) algorithm. The technique implementation is performed in MATLAB environment through industrial turbofan engines data treatment using C-MAPSS dataset.

The performance evaluation of the proposed technique is carried out by calculating performance metrics and comparing the obtained results. The achieved score of 7.29 is a satisfactory prediction. Compared with results from TCMN, CNN, MLP, SVR, and RVR, our proposed methodology proves to be a significant improvement but the Deep LSTM method remains the method offering the best prediction.

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