



# RUL Prediction with Encoding and Spatial-Temporal Deep Neural Networks

Amal Ayadi, Mohamed Amin Benatia, Ramzi Chaieb, Anne Louis

## ► To cite this version:

Amal Ayadi, Mohamed Amin Benatia, Ramzi Chaieb, Anne Louis. RUL Prediction with Encoding and Spatial-Temporal Deep Neural Networks. 2023 IEEE Smart World Congress (SWC), Aug 2023, Portsmouth, France. pp.1-7, 10.1109/SWC57546.2023.10449309 . hal-04553983

**HAL Id: hal-04553983**

**<https://hal.science/hal-04553983>**

Submitted on 25 Apr 2024

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# RUL Prediction with Encoding and Spatial-Temporal Deep Neural Networks

1<sup>st</sup> Amal AYADI

*CESI LINEACT*

*CESI Engineering School*

Rouen, France

aayadi@cesi.fr

2<sup>nd</sup> Mohamed Amin BENATIA

*CESI LINEACT*

*CESI Engineering School*

Rouen, France

mbenatia@cesi.fr

3<sup>rd</sup> Ramzi CHAIEB

*CESI LINEACT*

*CESI Engineering School*

La Rochelle, France

rchaieb@cesi.fr

4<sup>th</sup> Anne LOUIS

*CESI LINEACT*

*CESI Engineering School*

Rouen, France

alouis@cesi.fr

**Abstract**—The objective of this paper is to design and develop an approach to estimate the Remaining Useful Life (RUL) of an industrial equipment evolving in a Cyber-Physical System (CPS). To do so, this work aims to predict failures and malfunctions of an industrial equipment, as well as evaluating all the main underlying causes. The system will also identify the actions to be taken in order to maintain the system at a certain level of performance and guarantee that it will operate in the most efficient way, which implies a study of all aspects: reliability, availability and maintenance. Existing works are often limited to the estimation phase of the RUL, with only a few case studies (such as ball bearings and Proof Of Concept(PoC)) available and a significant lack of data. The innovation of this research work will be to design and develop diagnostic and prognostic approaches based on Deep Learning (DL)(e.g. Boltzmann Machine, Recurrent Networks and Echo State Network (ESN)) for the maintenance and health management of industrial equipment evolving in a CPS.

## I. INTRODUCTION

Following the fourth industrial revolution, referred to as *Industry 4.0* and first coined in the 2011 Hannover Fair [18], came the fifth's industrial revolution (*Industry 5.0*) with the goal to give more place to human being by taking advantage of the *Industry 4.0* developed technologies. The main objectives of this new revolution are : to achieve societal goals by placing humans in the center of the production process, to reduce the environmental impact by making production more cleaner and respectful of our planet, and to become more resilient and economical [1]. In addition, globalization introduces the mass personalization challenge, where billions of end-users will require more personalized and customized products [2]. In this context, Artificial Intelligence (AI), Internet of Things (IoT), and Cyber Physical Production Systems(CPPS) would be a driving force to combine human expertise to design precise control and cognitive abilities [3].

With the massive integration of smart technologies in manufacturing industries, researchers are observing an increased complexity and maintenance costs of production processes. In addition, with globalization and the need for more customized goods and less lead time, equipments must be more reliable & resilient. Basically, a big part

of the manufacturing processes assume that manufacturing assets are available continuously. However, practically machines can breakdown, or can stop working due to unknown failures [4]. Thus, manufacturing units should adopt Predictive Maintenance (PdM) to reduce maintenance costs, prevent failures and accidents, and increase transparency. [5]. More specifically, PdM processes can assess the health state of a manufacturing asset by estimating the RUL (Remaining Useful Life), and optimizes the maintenance plans based on those predictions. In *Industry 5.0*, PdM will assist maintenance operators in identifying potential future failures and support them by giving recommendations instead of performing planned and scheduled maintenance or corrective maintenance. Additionally, in *Industry 5.0*, there will be a focus on human factors by proposing new PdM design consideration that enhance human well-being and overall system performance [6].

The implementation of PdM systems involves setting up diagnostic and prognostic capabilities in near-real time [6]. Prognostics and Health Management (PHM) is an engineering discipline that aims to estimate the Remaining Useful Life (RUL) of a component or industrial equipment, which is the amount of time remaining before it stops performing its assigned task. The predicted RUL is then as used an indicator which allows production managers to establish a degradation curve of the equipment from the sensors collected data. Approaches to estimating RUL can be classified into two broad categories: Physics of Failures (PoF)-Based and Data-Driven. It is also possible to combine both approaches, giving rise to a third category of approaches called hybrid (or fusion) approaches. The work conducted in [19], shows the effectiveness of data-driven approaches and more specifically Deep Learning methods in predicting the RUL indicator. The authors state that several challenges need to be addressed by data-driven approaches, such as: the trend of complex equipment health degradation, noisy data from sensors, unavailability of data, and complex time dependency between sensor data. In this paper, a data-driven approach for RUL prediction based

on deep neural networks is proposed. The main contributions of this paper are :

- Reduce processing time, through the use of an encoding phase that reduces the number of features to be learned,
- Allow real-time health assessment, by reducing the latency between data collection and RUL estimation,
- Enhance RUL prediction accuracy, by taking into consideration spatial and temporal features of the collected signal,

The rest of this paper is organized as follows. Section II provides an overview of related works. In section III, we explain the concepts and architecture of the proposed model to predict the RUL of a system using sensor data. In Section IV, we briefly present the used dataset, the main obtained results and a discussion regarding the evaluation criteria used. Finally, Section V concludes this paper and gives an outlook on future work.

## II. RELATED WORKS

PHM is a multidisciplinary field that involves the use of data, models, and algorithms to predict the RUL of a system and to optimize its maintenance [7]. The goal of PHM is to improve the safety, reliability. The approaches used to estimate the RUL can be classified into two broad families : PoF-Based and Data-Driven approaches. PoF-based approaches involve the use of physical models, such as finite element models, to understand the underlying mechanisms of a system's degradation and predict its RUL. While the Data-Driven approaches, While the Data-Driven approaches the historical data (generally collected from sensors and other sources) to model the health of a system and predict its RUL. Techniques such as statistical modeling, machine learning, and signal processing are commonly used in this area. Finally, a hybridization between the two approaches can be performed to improve the accuracy of RUL prediction, and allow end-users to interpret the results. Finally, these methods are typically employed to optimize maintenance operations by utilizing PHM information to schedule and execute maintenance activities in an optimized manner. Some of the techniques used for this purpose include condition-based maintenance and reliability-centered maintenance. In this context, PHM was applied to a wide range of systems, including aircraft, wind turbines, batteries, and engines [15] [16]. A literature review would present case studies of PHM in various applications, including those mentioned earlier. However, the field of PHM is still relatively new, and there are many challenges that need to be overcome. These challenges can include issues related to data quality, feature selection, and model validation. Overall, PHM is a multidisciplinary field that is still evolving, but it has the potential to bring significant benefits to various industries. Data-driven techniques, specifically AI and Deep Learning, are increasingly being used in the manufacturing sector due to the growth of the Industrial Internet of Things (IIoT) and

Big Data [3]. DL techniques, in particular, are increasingly being utilized in the area of RUL prediction because they have the capability to automatically extract features from complex and high-dimensional data and make predictions without the requirement for manual feature selection or explicit model equations. In this context, Wang et al. [8] claims that the current state-of-the-art DL approaches used for RUL prediction, can significantly improve the reliability and the safety of industrial components or systems, prevent breakdowns, and reduce maintenance costs.

The four main representative Deep Learning architectures discussed in this paper include Auto-Encoder (AE), Deep Belief Network (DBN), Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN). Finally, authors state that Deep Learning-based RUL prediction approaches are purely data-driven, thus a large database of run-to-fail trajectories is needed to increase user confidence. Additionally, combining Deep Learning with other data-driven or physics-based approaches may provide more effective and precise results. An example of the use of DL techniques in RUL prediction can be found in [9]. In their paper, Deutsch et al. present a Deep Learning-based approach, DBN-FNN, to predict the RUL of rotating equipment using vibration data [9]. They showed that the DBN-FNN algorithm achieved a slightly better accuracy for gear RUL prediction but slightly worse accuracy than a particle filter-based approach. The DBN-FNN does not require manual feature extraction and explicit model equations, making it a promising approach for RUL prediction of rotating components with big data. However, the main limitation of this paper is that the DBN-FNN algorithm still needs further improvement to achieve more accurate predictions. Additionally, the algorithm is limited to the specific use case of RUL prediction of rotating equipment using vibration data, so it may not be suitable for other types of equipment or data. Another limitation is that this algorithm needs a certain amount of data to learn from it, otherwise, the predictions can be inaccurate. Another example can be found in [10], where authors present a novel deep learning-based prognostic method for the estimation of machine degradation status. This approach differs from previous state-of-the-art methods in that it utilizes a combination of short-time Fourier transform and multi-scale feature extraction with convolutional operation to extract relevant information from raw data. This allows for a more efficient and effective representation of the data, leading to improved performance in the estimation of machine degradation status. The limitations of the proposed deep learning-based method for prognostics in the paper are the need for sufficient labeled training data, which is a general requirement for data-driven approaches, especially for prognostic problems. Additionally, the authors mention that while the proposed method is promising, it could be further optimized by using techniques such as SqueezeNet to reduce network parameters without loss of performance and the Short

Frequency Fourier Transform (SFFT) to reduce computational burden and memory resource while keeping the resolution. These will be investigated in future works.

As seen in the previous papers, DL models, including those used for prognostics, can have several limitations. One limitation is the need for a large amount of labeled data to train the model, which can be difficult and time-consuming to acquire. Additionally, deep learning models can be computationally expensive, which can be an issue for real-time or resource-constrained applications. Another limitation is that DL models can be difficult to interpret and understand, which can make it challenging to diagnose and correct errors. Additionally, DL models are not robust to noise and outliers, which can affect the performance of the model. Furthermore, deep learning models tend to generalize poorly, meaning that they may not perform as well on unseen data. Finally, DL models can be affected by the curse of dimensionality, meaning the model's performance decreases when the number of features or dimensions increases. One potential solution to this limitation is to use Auto-encoders as an embedding algorithm to generate synthetic data. Auto-encoders are neural networks that can learn the underlying structure of the input data and can be used to generate new, synthetic samples. By using Auto-encoder to generate synthetic data, it may be possible to overcome the limitation of limited labeled data, and improve the performance of the deep learning-based prognostic method. Moreover, Auto-encoder can also be used as an embedding algorithm, meaning it can transform the data into a lower-dimensional representation that can be used as input for other machine learning models. This can also help to overcome the curse of dimensionality, which is another limitation of deep learning models.

### III. PROPOSED APPROACH

#### A. Auto-encoders & State Space Models

The proposed methodology employs a data-driven approach to predict the RUL of a system using sensor data. The process is divided into two key steps: feature extraction and regression (time series forecasting). In the feature extraction step, relevant features are extracted from the sensor data using embedding models, specifically Auto-encoders (AE). The extracted features are then used in the regression step to estimate the RUL using a State Space Model (SSM), a widely used family of models in statistical signal processing and time series analysis.

Auto-encoders are particularly useful in the feature extraction step as they enable efficient processing of large-scale sequential data while discovering a more efficient and compressed representation of the sensor data. An Auto-encoder is a neural network architecture designed to learn an identity function in an unsupervised manner. The encoder network compresses the high-dimensional input data into a low-dimensional code, and the decoder network then recovers the data from the code, with a larger output layer.

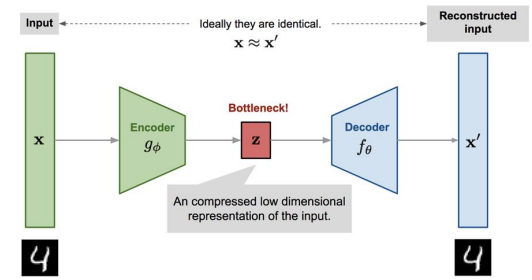


Fig. 1. Architecture of the AutoEncoder

This approach is particularly useful for systems where sensor data is high-dimensional and complex, as it allows for efficient processing of the data while still extracting relevant features. The model contains an Encoder function, parameterized by  $\phi$ , to learn the low dimensional code  $Z$ , a decoder function, parameterized by  $\theta$ , that reconstructs the original input  $X$  from the lower dimensional code  $Z$  as shown in Figure 1. Additionally, the use of SSM in the regression step allows for the modeling of dynamic systems, making the approach suitable for a wide range of applications in various industries.

#### B. Proposed architecture

The proposed architecture for estimating RUL of a turbofan is motivated by the need for accurate and efficient prediction of the RUL of these systems. The ability to predict RUL can help with maintenance planning and scheduling, reducing downtime and prolonging the life of the equipment.

The proposed architecture is depicted in Figure 2. The architecture combines several key components to effectively analyze sensor data and make predictions. The use of an Auto-encoder allows for the efficient compression and encoding of the sensory data, reducing the dimensionality and identifying important features. The LSTM layer then takes the encoded data and extracts temporal features, allowing for the analysis of patterns and trends over time. The attention mechanism provides weights on the LSTM output, allowing the model to focus on the most relevant information for RUL estimation. Finally, a fully connected layer with a regression layer uses this information to make the final RUL prediction.

One of the advantages of this architecture is that it can effectively handle time-series data, which is crucial for RUL prediction as the sensor data is collected over time. Additionally, the use of an auto-encoder and LSTM layer enables the model to extract features and patterns from the data, which is important for accurate RUL predictions. The attention mechanism provides the ability to focus on the most important features, which can improve the prediction accuracy. Furthermore, the architecture is flexible and can be easily adapted to different types of sensor data and equipment.

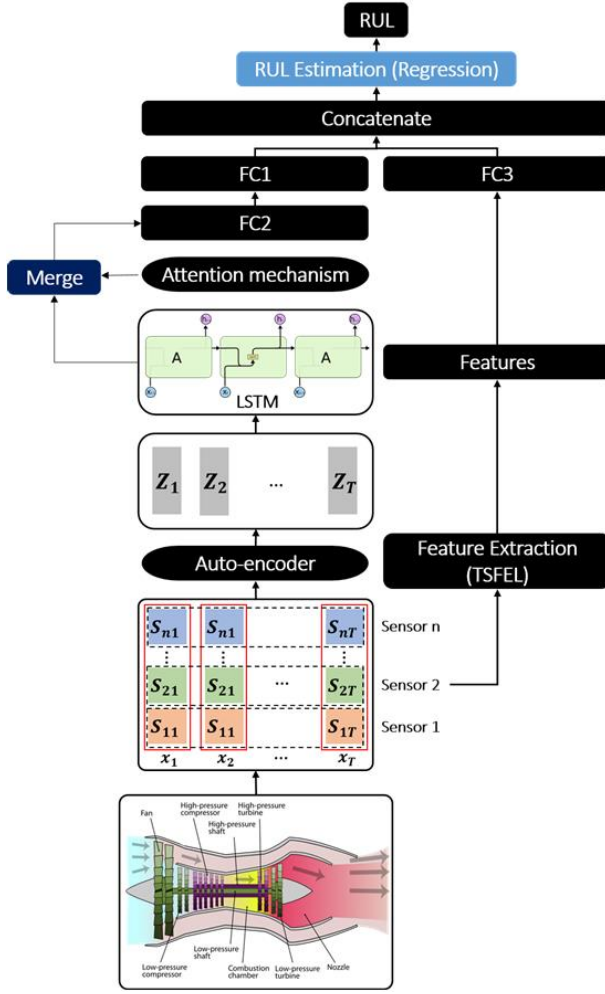


Fig. 2. Architecture of the proposed model

### C. Evaluation criteria

To evaluate the accuracy of the proposed RUL prediction method, two commonly used evaluation criteria have been adopted: the Root Mean Square Error (RMSE) and the scoring function. The RMSE is a widely accepted measure of the difference between the predicted and actual RUL values. A lower RMSE value indicates a higher level of accuracy in the prediction.

The scoring function used in the evaluation of the proposed RUL prediction method was adopted from the PHM data challenge 2008, an annual competition that encourages the development of innovative techniques for PHM of engineered systems. The specific challenge in 2008 was to predict the RUL of turbofan engines using sensor data. The competition involved a dataset that consisted of run-to-failure data from 21 turbofan engines. The goal was to predict the RUL of each engine using data from the sensors, with the best-performing methods being evaluated using the scoring function.

The scoring function used in the challenge evaluated the

accuracy of the predicted RUL values, as well as the computational efficiency of the method. The function took into account the difference between the predicted and actual RUL values, the time taken to provide a prediction, and the uncertainty in the predicted RUL values. Therefore, by adopting this scoring function in the evaluation of the proposed RUL prediction method, the method's accuracy and practicality could be assessed in a comprehensive manner that reflects real-world scenarios.

In summary, by using both the RMSE and the PHM data challenge-based scoring function as evaluation criteria, the performance of the proposed RUL prediction method can be thoroughly evaluated from both an accuracy and practicality perspective. The RMSE is used to evaluate the accuracy of the predicted RUL values, while the PHM data challenge-based scoring function evaluates both the accuracy and the practicality of the proposed method, taking into account factors such as computational efficiency and uncertainty in the predicted RUL values.

## IV. RESULTS & DISCUSSION

### A. Used Dataset

PHM techniques, such as predicting the RUL of engineered systems, have a wide range of applications in industry. These techniques can be used to improve safety, reliability, and efficiency in applications such as aerospace, energy, transportation, and manufacturing. By accurately predicting the RUL of critical components, operators can schedule maintenance activities more efficiently and minimize downtime. For example, predicting the RUL of aircraft engines can help to minimize maintenance costs and ensure the safety of both crew and passengers. Similarly, predicting the RUL of a vehicle's battery can help to optimise efficiency and reduce the risk of unexpected failure.

The proposed approach is evaluated using the widely used Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) dataset. Specially, we use the C-MAPSS turbofan engine dataset used in the PHM data challenge 2008 [15] [16] that contains sensor data from 21 turbofan engines. The engines were operated under various conditions, and the sensor measurements were taken at different points in time. The data includes both time-series sensor measurements and data from the last measurement of each engine.

The sensor measurements in the dataset include a wide range of parameters, including pressure, temperature, and vibration. Some specific examples of the sensor measurements include:

- Total temperature at the front of the compressor
- Total pressure at the front of the compressor
- Physical fan speed
- Vibration measurements at various locations on the engine

The sensor data in the C-MAPSS dataset is considered to be realistic and representative of the data that would be available

in real-world applications. The goal of the PHM data challenge was to use this sensor data to predict the RUL of the engines, with the best-performing methods being evaluated using the scoring function.

Overall, the C-MAPSS turbofan engine dataset is a valuable resource for researchers working on PHM, and has been used in numerous studies on the development and evaluation of methods for predicting the RUL of engineered systems.

Two subdatasets, FD001 and FD004, are chosen for evaluation, with FD001 being the simplest and containing only one operation condition and one faulty type, while FD004 is the most complicated, containing six operation conditions and two faulty types. Both subdatasets have training and testing files, with the training file recording sensor data for a certain number of engines during the run-to-fail experiments, and the testing file containing sensor measurements for a certain number of engines during certain running cycles.

### B. Experiment configuration

To evaluate the performance of our proposed algorithm for predicting RUL, we compared it with a recently published DL algorithm that utilized an attention-based and LSTM approach [11]. We also report the training and testing times for both algorithms. The experiments were conducted on an Ubuntu 18.04 server equipped with an Intel(R) Core (TM) i9-9980XE HQ processor running at 4.40 GHz, as well as 4 GeForce NVIDIA RTX 2080 graphics cards with 11 GB each and 128 GB of RAM. TABLE I displays the results, indicating that our proposed approach using learning-based methods requires significantly less time for both training and testing compared to the baseline model. This is due to the data reduction achieved with the Auto-encoder. Notably, the proposed approach boasts the lowest training time, taking only 16.33 minutes in FD001 dataset and 24.31 minutes in FD004 dataset.

TABLE I  
RUNNING TIME ALGORITHMS

Algorithms running time /minutes	Dataset	
	FD001	FD004
Attention-based and LSTM approach [11]	22.53	41.77
Proposed algorithm	16.33	24.31

### C. Obtained results & Discussion

We first present the performance indicators of the Auto-encoder model. As stated before, an Auto-encoder is a neural network used for solving unsupervised learning tasks such as dimensionality reduction, feature extraction, and data compression. The performance of an Auto-encoder is typically measured by its train and validation loss. The train loss is the error between the predicted output and the actual output on the training set, while the validation loss is the error on a separate validation set. The train/validation loss and accuracy's

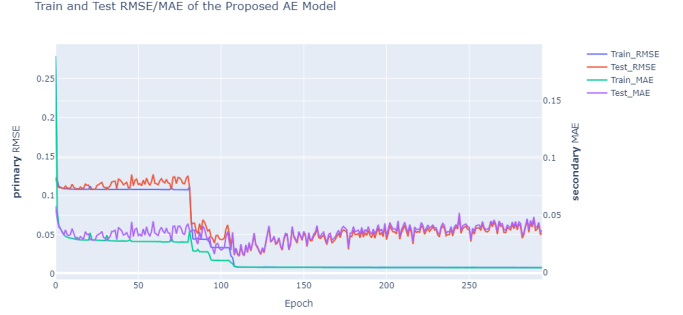


Fig. 3. Performance metrics of the proposed AutoEncoder

curves are shown in Figure 3. We can notice that the Auto-encoder has a low training and validation loss, indicating that it has learned to accurately reconstruct the input data. We also observe that the small gap between the training and validation loss indicates a well-performing Auto-encoder.

TABLE II  
MAIN OBTAINED RESULTS

Evaluation criteria	Dataset	
	FD001	FD004
RMSE	15.62	31.1814
Score	434.1828	46550.66

In addition, we evaluate the RUL prediction accuracy of the proposed model by using the standard RMSE and scoring function given in the 2008 PHM Data challenge (i.e., Early Prediction Score). Therefore, the average RMSE was calculated based on the predicted RUL and the ground truth as in Eq. 1, where  $RUL_{Truth}^i$  is the ground truth for gas turbine  $i$ ,  $RUL_{Pred}^i$  is the predicted RUL for gas turbine  $i$ , finally  $N$  denotes the number of existing gas turbines.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (RUL_{Truth}^i - RUL_{Pred}^i)^2} \quad (1)$$

In the other hand, we use the *Early Prediction Scoring Function* [17] which is a metric applied to prognostic tasks. This scoring function, given by Eq. 2, will penalizes late prediction than the early ones. The scoring function is given as follow:

$$s = \begin{cases} \sum_{i=1}^N \exp^{\frac{-d_i}{13}} - 1 & \text{if } d_i < 0 \\ \sum_{i=1}^N \exp^{\frac{d_i}{10}} - 1 & \text{if } d_i > 0 \end{cases} \quad (2)$$

where  $d_i$  represents the difference between the predicted RUL and the ground truth (i.e.,  $d_i = RUL_{Truth}^i - RUL_{Pred}^i$ ). The main experimental results of the proposed approach are shown in TABLE II. TABLE III presents the experimental outcomes of some other state-of-the-art techniques on the two datasets. In general, the performance of various methods



TABLE III  
EXPERIMENTAL RESULTS ON THE FD001 AND FD004 DATASETS [11]

	Criterion	Statistic	Shallow Learning					Deep Learning			
		Cox's regression [12]	MLP [13]	SVR [13]	RVR [13]	ELM [14]	RF [14]	CNN [13]	LSTM [11]	VAE+RNN [14]	RVE [14]
FD001	RMSE	45.10	37.56	20.96	23.80	17.27	17.91	18.45	14.53	15.81	13.42
	Score	28616	17972	1381.5	1502.9	523.00	479.75	1286.7	322.44	326	323.82
FD004	RMSE	54.29	77.37	45.35	34.34	38.43	31.12	29.16	27.08	26.54	16.37
	Score	1164590	5616600	371140	26509	121414.47	46567.63	7886.4	5649.41	5634	1845.99

exhibits a notable discrepancy between the FD001 and FD004 datasets. This disparity can be attributed to the differing characteristics of the datasets. Specifically, the FD001 dataset is relatively straightforward, with a single operational condition and a single failure mode. In contrast, the FD004 dataset contains a considerably larger number of engines for testing, with a total of 248 engines, which is significantly more than the number of engines in the FD001 dataset. As a result, the cumulative scores for all engines in the FD004 and FD001 datasets differ significantly in magnitude, highlighting the importance of dataset complexity when evaluating the effectiveness of various methods.

The effectiveness of the proposed approach in predicting the RUL has been demonstrated, as evidenced by its superior performance relative to the majority of benchmark approaches. Furthermore, the proposed approach exhibits the shortest running time for RUL prediction, outperforming even the best and most recent benchmark approaches [11]. This combination of high accuracy and computational efficiency underscores the potential utility of the proposed approach in practical applications where real-time RUL prediction is critical.

The proposed approach's superior computational efficiency in predicting the RUL compared to other benchmark approaches enables more rapid and precise RUL predictions. This capability can have significant implications for maintenance operations, as it allows maintenance personnel to plan and implement maintenance activities with greater speed and accuracy. As a result, downtime can be reduced, and overall equipment reliability can be improved, leading to greater operational efficiency and cost savings for the organization.

## V. CONCLUSION

In summary, the proposed data-driven approach for RUL prediction using deep neural networks offers several significant advantages. By integrating an encoding phase, the processing time is reduced, enabling real-time health assessment with minimal latency between data collection and RUL estimation. Moreover, the approach incorporates both spatial and temporal features of the signal, resulting in improved RUL prediction accuracy. Overall, this approach has the potential to enhance the reliability and effectiveness of predictive maintenance in diverse industries, including aerospace, manufacturing, and healthcare. By reducing processing time and allowing real-time health assessment, potential equipment failures can be

detected in advance, reducing downtime and maintenance costs. Additionally, enhanced RUL prediction accuracy can improve maintenance scheduling and enhance safety by identifying potential equipment failures before they cause accidents or harm to individuals. Nonetheless, challenges such as the requirement for high-quality input data and adequate computational resources remain. Further research is necessary to fully realize the potential benefits of this approach and overcome its limitations, such as addressing interpretability and explainability issues and optimizing the trade-off between prediction accuracy and computational efficiency.

## REFERENCES

- [1] Xu, Xun, et al. "Industry 4.0 and Industry 5.0—Inception, conception and perception." *Journal of Manufacturing Systems* 61: 530-535, 2021.
- [2] Maddikunta, Praveen Kumar Reddy, et al. "Industry 5.0: A survey on enabling technologies and potential applications." *Journal of Industrial Information Integration* 26, 2022.
- [3] Verma, Ashwin, et al. "Blockchain for Industry 5.0: Vision, Opportunities, Key Enablers, and Future Directions." *IEEE Access* 10, 2022.
- [4] Maddikunta, Praveen Kumar Reddy, et al. "Industry 5.0: A survey on enabling technologies and potential applications." *Journal of Industrial Information Integration* 26, 2022.
- [5] Van Oudenhoven, Bas, et al. "Predictive maintenance for industry 5.0: behavioural inquiries from a work system perspective." *International Journal of Production Research*, 2022.
- [6] Maqbool, Fariha, Haroon Mahmood, and Hasan Ali Khattak. "An Efficient Fault-Prediction Mechanism for Improving Yield in Industry 5.0." *24th International Multitopic Conference (INMIC)*. IEEE, 2022.
- [7] Pecht, M., & Gu, J. Physics-of-failure-based prognostics for electronic products. *Transactions of the Institute of Measurement and Control*, 31(3-4), 309-322, 2009.
- [8] Wang, Y., Zhao, Y., & Addepalli, S. Remaining useful life prediction using deep learning approaches: A review. *Procedia manufacturing*, 49, 81-88, 2020.
- [9] Deutsch, Jason, and David He. "Using deep learning-based approach to predict remaining useful life of rotating components." *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 48.1, 2017.
- [10] Li, X., Zhang, W., & Ding, Q. "Deep learning-based remaining useful life estimation of bearings using multi-scale feature extraction". *Reliability engineering & system safety*, 182, 208-218, 2019.
- [11] Chen, Z., Wu, M., Zhao, R., Guretno, F., Yan, R., & Li, X. . Machine remaining useful life prediction via an attention-based deep learning approach. *IEEE Transactions on Industrial Electronics*, 68(3), 2521-2531, 2020.
- [12] PHAM, Hong Thom, YANG, Bo-Suk, NGUYEN, Tan Tien, et al. Machine performance degradation assessment and remaining useful life prediction using proportional hazard model and support vector machine. *Mechanical Systems and Signal Processing*, vol. 32, p. 320-330, 2012.
- [13] G. S. Babu, P. Zhao, and X.-L. Li, "Deep convolutional neural network based regression approach for estimation of remaining useful life," in *Proc. Int. Conf. Database Syst. Adv. Appl.*, 2016, pp. 214–228.

- [14] Costa, Nahuel, and Luciano Sánchez. "Variational encoding approach for interpretable assessment of remaining useful life estimation." *Reliability Engineering & System Safety* 222 (2022): 108353.
- [15] A. Saxena, K. Goebel, D. Simon, and N. Eklund, "Damage propagation modeling for aircraft engine run-to-failure simulation," in *Proc. Int. Conf. Prognostics Health Manage.*, pp. 1–9, 2008.
- [16] A. Saxena and K. Goebel, "PHM08 challenge data set," NASA AMES Prognostics Data Repository, Moffett Field, CA, USA, Tech. Rep., 2008.
- [17] G. S. Babu, P. Zhao, and X.-L. Li, "Deep convolutional neural networkbased regression approach for estimation of remaining useful life," in *Proc. Int. Conf. Database Syst. Adv. Appl.*, 2016, pp. 214–228.
- [18] Messe, Deutsche. "Hannover Messe 2011." *Engineering and Technology* 6.3 (2011): 90-90.
- [19] Gugulothu, Narendhar, et al. "Sparse neural networks for anomaly detection in high-dimensional time series." *AI4IOT workshop in conjunction with ICML, IJCAI and ECAI*. 2018.