CONVOLUTIONAL AND LONG SHORT-TERM MEMORY NEURAL NETWORKS BASED MODELS FOR REMAINING USEFUL LIFE PREDICTION

Katerina M. Gritsyuk, Vera I. Gritsyuk*

[1] National Technical University "Kharkiv Polytechnic Institute“, Kharkiv
[2] Kharkiv Institute of State University of Telecommunications, Kharkiv
Ukraine

* Corresponding Author, e-mail: prichkoel12@gmail.com

Abstract: The development of industry leads to the growth of the complexity of equipment used in enterprises. Corrective and preventive maintenance are replaced by predictive maintenance. Predicting the remaining useful life of equipment with high accuracy allows carry out repairs or replacement of equipment in terms maximally near to its failures. It will allow increase the reliability and safety of systems, and reduce maintenance costs. In Industry 4.0 conception the most preferable are approaches based on processing of large amounts of data using machine learning methods. In this study it is proposed deep learning models based on convolutional and long short-term memory neural network which allow to improve prediction accuracy. The high efficiency of proposed models is demonstrated by comparison with other models used in predicting of remaining useful life of aero engines.

Key words: predictive maintenance, remaining useful life, aero engine, convolutional neural network, long short-term memory network.

1. INTRODUCTION

Maintenance of equipment and prognostics are important in many industry areas, for example: manufacturing, automotive, aerospace, heavy industry and others. When the traditional corrective maintenance and scheduled preventive maintenance [1] can satisfy the need for efficiency and reliability less and less, intelligent prognostic and health management (PHM) technologies are becoming desirable for industry application [2]. The purposes of PHM are increasing of the operational availability, improvement of system reliability and safety, decreasing of maintenance costs when it is monitoring the facility conditions. The classical system of preventive maintenance of the equipment of the enterprise loses its effectiveness and does not answer modern requirements. The role of methods for predicting the technical condition and remaining useful life (RUL) of equipment is increasing. This strategy is called predictive maintenance (PdM). Decisions made on the basis of reliable predictions of RUL ensure compliance of a balance between the cost of repairs and the value of the potential damage and risks from equipment failure. Recently, when introducing the Industry 4.0 concept for building prediction models for PdM the most promising approaches are based on processing large amounts of multidimensional sensor data and using machine learning methods.

RUL can be predicted based on history data. That is important for enhancement maintenance schedules to avoid failures and reduce the resulting costs [3]. This study proposes novel deep learning models for RUL estimation of aero-engine.

RUL prediction contributes to system health management, it can improve the development of the degradation warning systems and failure detection with high accuracy. RUL prediction is a problem because there are uncertainties arising during this process. The governments of many countries support the development of the RUL prediction process. The understanding of RUL prediction becomes better in the last years because the technologies are improved.

The purpose of this study: researching of different methods for prediction RUL of turbofan engine; choice data set for experiments, executing data preprocessing; building hybrid deep learning models based on convolutional neural network (CNN) and long short-term memory (LSTM) network; with the help of metrics RMSE, MAE, Score evaluate models; choice the model which can better predict RUL of turbofan engine. Technologies, methods of deep learning help predict RUL of equipment, its failures time with greate accuracy, reduce downtime of equipment. This allows reduce losses in systems using machines, increase safety of them.

2.BASIC METHODS AND MODELS

The existing methods for PdM are subdivided into three main groups: data-driven approaches, model-based approaches and hybrid approaches. Model-based methods are more accurate if the system degradation is modeled exactly [4], they require general prior knowledge about physical systems. Model-based methods use mathematical models to describe the physical behavior and degradation processes of equipment, while the parameter values are changed based on the collected data [5]. They are usually unavailable in practice. Popular model-based methods include particle filter, Weibull distribution, Eyring model, the Markov process model, the Wiener process model, the Gaussian mixture model, etc. The main disadvantage of the model-based methods is the need for regular structural and parametric optimization of models due to the dynamically changing of environment [6]. Complex systems require significant costs for the creation and configuration of the model-based methods, including the involvement of experts [7].

The data-driven methods can model the degradation characteristics based on historical sensor data. The main correlations in the data of sensor can be discovered, and the information about the RUL can be obtained. Methods based on the use of data have been proposed and are currently being actively developed. Data-driven methods have the properties of universality, because they are abstracted from the physical nature of objects, they do not require knowledge of internal structure of objects and functional connections between elements [8]. Data-driven methods can be built on the basis of classical machine learning algorithms such as support vector machines, random forest, decision trees, gradient boosting, k-nearest neighbors, etc. But application of these methods is criticized when solving the forecasting tasks, because the methods give poor results when processing large complex multidimensional sensors data. In addition, these classic machine learning models are usually based on a feature engineering process (feature engineering). The most perspective is the use of artificial neural networks for PdM [9]. When it is processing large amounts of data, a neural network execute feature extraction much better than human.

Data-driven and model-based methods show advantages in the different tasks. However actual fault data are difficult to get because it takes a lot of time and it is expensive. The commercial modular aero-propulsion system simulation (C-MAPSS) data set provided by Nasa was proposed for estimation of RUL of aero-engines in [10]. Turbofan engine is the complex and precise thermal equipment, it is the basis of the aircraft. About 60% of the aircraft faults are connected with the turbofan engine [11]. The RUL prediction of the turbofan engine is foundation for PdM. Thanks to the quick development of machine learning, the efficiency of turbofan engines has been greatly increased.

Operation process of turbofan engine cannot be detached from the detailed influence of internal factors - physical and electrical characteristics and external factors - temperature and humidity [12]. The data obtained by the operation process of turbofan engine have the characteristics of nonlinearity, time-varying, large scale and high dimension, which lead to failures in correct feature extraction.

Many models developed to estimate the RUL of turbofan engines. Two approaches for the solution of this problem – model-based and data-driven approaches to predict RUL of aircraft engines, are used in [13]. The authors used non-linear and linear prediction models. The general statement and algorithm to solve this problem are provided. In every project data of sensors is used, when the technology of sensors developed. In [14] it was proposed semi-supervised learning models for RUL estimation to reach high RUL prediction accuracy. In [15] authors proposed auto-regressive integrated moving average (ARIMA) model and SVM algorithms to estimate RUL of turbofan engines.

Well known CNN based approaches are widely applicable and give good results in RUL prediction. Feature extraction capacity of CNN is big. They can extract local features, working up the data with multiple working conditions and faults [16]. The one-dimensional CNN can be used to the time series analysis of data generated by sensors. In [17] authors proposed a RUL prediction method, which model was based on the architecture of dual CNN. The first CNN model defines the failure point, with the help of the second CNN model the RUL prediction was executed. The feature extraction is not need in this method. The vibration signals have been received, useful information have been preserved. The results of prediction and evaluation of model demonstrated the effectiveness of this method. In [18] authors used several deep learning models to classify the degradation stages. In this way it was predicted the RUL of components. In [19] authors proposed a new data-driven method which used deep convolutional neural networks (DCNN) for prediction, time windows was used and experiments were executed on the C-MAPSS dataset.

LSTM is a kind of recurrent neural network (RNN), which solve the problems of gradient disappearance and gradient explosion in RNN. LSTM cell have the structure of three gates. This is permit to take a long range of dependence, work time series data. The prediction of RUL of turbofan engine needs to work the time series data and LSTM receives the necessary features from the time series data which were generated by the turbofan engine. In [20] authors used a method which was based on LSTM network. That method watched the system degradation process and helped to predict the RUL.

The new prediction models - hybrid models, which combines two or more neural network models, were been proposed. In [21] authors proposed a hybrid model that arranges the advantages of the auto-encoder and the bidirectional LSTM (BLSTM) neural network. The auto-encoder was used as a tool for feature extraction, and the BLSTM fixes the characteristics of the bidirectional dependences in data. This method was applied on the C-MAPSS data set to test the accuracy and effectiveness.

3. NETWORK STRUCTURES PROPOSED IN STUDY

In this study we proposed some combinations of CNN and LSTM networks for RUL prediction.

CNN is a special architecture of artificial neural networks. It is the best tool for image and video processing. They have a high capacity of extracting information from data thanks to sliding convolutional filters on two-dimensional input data. In PdM, the collected sensor data has a spatial structure, 2D-structure as in images. That is why CNN is used in this area. A simple CNN architecture consists of a convolution layer, a pooling layer and a fully connected layer. CNN models are used to solve the RUL predicting task based on multivariate time series data. A simple CNN model structure is shown in Fig. 1.

LSTM networks are variety of recurrent neural network (RNN). LSTM networks have a repeating module structure similar to standard RNN, but their structure is more complex than standard RNN. LSTM modules have three interacting special layers: input gate, forget gate, output gate.

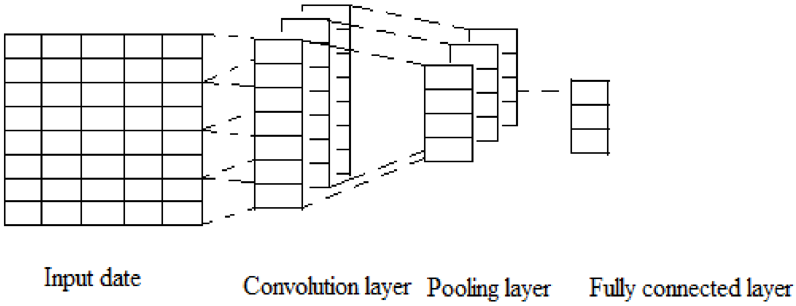


Figure 1. Structure of CNN model

The structure of the LSTM module is shown in Fig. 2. Thanks to this structure, LSTM modules remember information received over long periods of time. LSTM network are a good tool for modeling multivariate time series data, such as forecasting RUL of lithium-ion batteries and others.

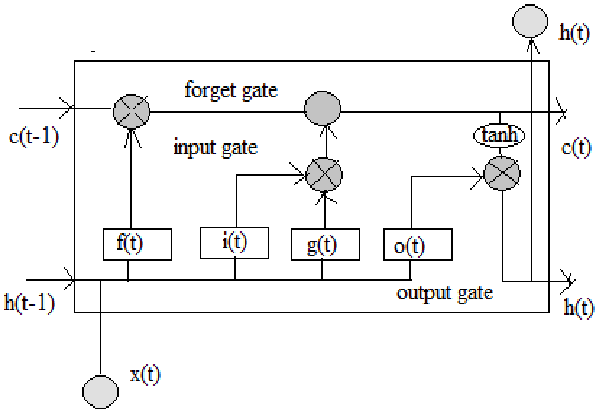


Figure 2. Structure of LSTM module

The state of the LSTM module at time t can be described by the equations presented below. Input gate i (t) runs what information will be transmitted to the memory cell using previous output and current sensor measurement data. Forget gate f (t) runs how the cell will be renewed. Output gate o(t) runs which information will be given to next time-step:

$$f(t) = \sigma(W_{xf} x(t) + W_{hf} h(t-1) + W_{cf} (t-1) + b_f), \quad (1)$$

$$i(t) = \sigma(W_{xi} x(t) + W_{hi} h(t-1) + W_{ci} c(t-1) + b_i), \quad (2)$$

$$g(t) = \tanh(W_{xg} x(t) + W_{hg} h(t-1) + b_g), \quad (3)$$

$$c(t) = f(t) \otimes c(t-1) + i(t) \otimes g(t), \quad (4)$$

$$o(t) = \sigma(W_{xo} x(t) + W_{ho} h(t-1) + W_{co} c(t) + b_o), \quad (5)$$

$$\hat{h}(t) = o(t) \otimes \tanh(c(t)), \quad (6)$$

where W – weight matrix, b – bias vector, $x(t)$ - is the input in time t, $\otimes$ - the element-wise multiplication, $\hat{h}(t)$ - the estimation value of LSTM module output.

In many tasks, a combination of different models is used to improve the predicting accuracy of RUL, because each individual model has its own shortcomings and limitations. The hybrid model CNN-LSTM is proposed in this study, which gives good results in predicting the RUL of turbofan engines. Since we have measurements from many sensors, we place the CNN-layers before the LSTM-layers. CNN is used for feature extraction and LSTM is used for interpretation of functions on time steps. Deep neural networks (DNN) will train the regression model to predict RUL. The DNN structure with one CNN layer and LSTM layer for predicting the RUL of turbofan engines is shown in Fig. 3.

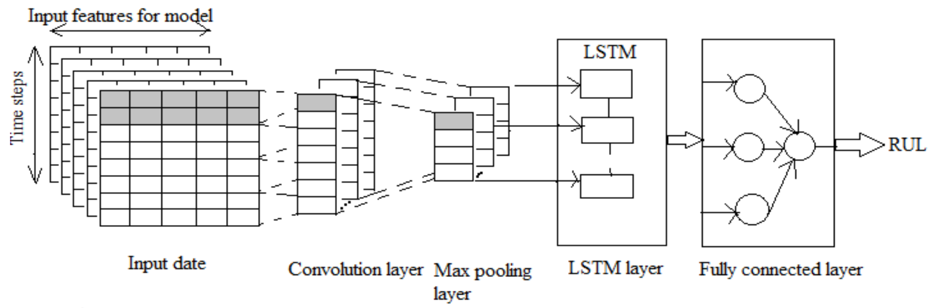


Figure 3. Structure of CNN-LSTM network model

In this study, we propose the CNN-LSTM-encoder-decoder model for predicting the RUL of gas turbine engines also. We create a hybrid CNN-LSTM-encoder-decoder model, in which CNN can be used as the encoder in the encoder-decoder architecture, the decoding process is performed by LSTM-decoder. In this study, the CNN-encoder architecture contains two convolutional layers, max pooling layer, flatten layer, repeat vector layer. LSTM-decoder contains two LSTM-layers, Time distributed wrapper, fully connected later. The structure of the CNN-LSTM-encoder-decoder model with one CNN layer and LSTM layer is shown in Fig. 4.

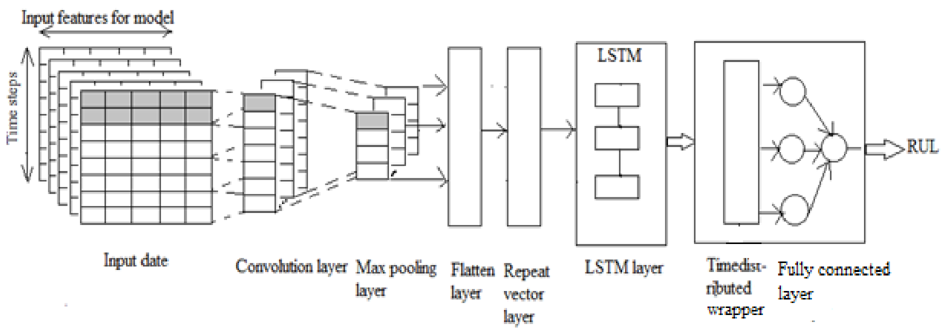


Figure 4. Structure of CNN-LSTM-encoder-decoder network model

CNN-Bidirectional LSTM (CNN-BLSTM) and CNN-Bidirectional GRU (CNN-BGRU) are next proposed models in this study. The Bidirectional LSTM is a model that consists of two LSTM layers. An input sequence enters the input of one layer in the forward direction, and the input of another layer in the backward direction. The outputs of the two layers are concatenated at each time step. This structure allows the network to receive information about the input sequence in the forward and backward direction. This increases the amount of information available to the network. The structure of the CNN-BLSTM network with one convolution layer and bidirectional layer is shown in Fig. 5.

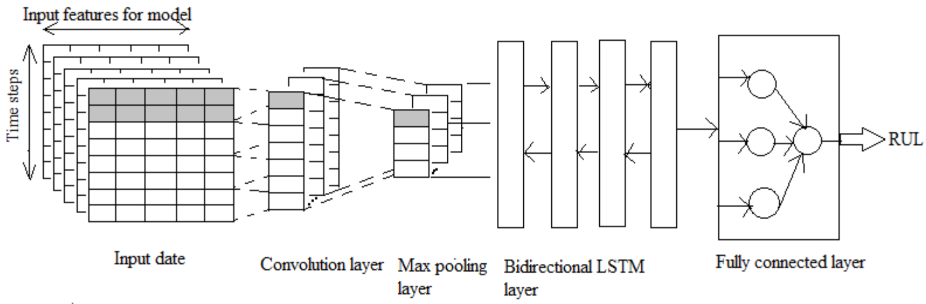


Figure 5. Structure of CNN-BLSTM network model

Bidirectional Gated Recurrent Unit (BGRU) – the model consists of two GRU layers. GRU cell consists of reset r(t), update z(t) gates. The combination of the new input with the previous memory determines with the help of reset gate r(t). The decision about how much of the previous memory information is retained to calculate the new state is performed by update gate z(t). The state of the GRU cell at any time t can be described by the formulas:

$$r(t) = \sigma(W_{xr}x(t) + W_{hr}h(t-1) + b_r), \tag{7}$$

$$z(t) = \sigma(W_{xz}x(t) + W_{hz}h(t-1) + b_z), \tag{8}$$

$$\tilde{h}(t) = \tanh(W_{x\tilde{h}}x(t) + W_{h\tilde{h}}(r(t) \otimes h(t-1) + b_{\tilde{h}}), \tag{9}$$

$$\hat{h}(t) = (1 - z(t)) \otimes \hat{h}(t-1) + z(t) \otimes \tilde{h}(t), \tag{10}$$

where W- weight matrixes, b-biases, $\otimes$ -element-wise multiplication, $x(t)$ - is the input in time t, $\hat{h}(t)$ - the estimation value of GRU module output.

4. EXPERIMENTS AND RESULTS

4.1. Dataset

The FD001 dataset from the C-MAPSS Dataset was selected for the experiments. It contains a set of sensor measurements in flight that imitate the behavior of similar aircraft turbine engines and their operational conditions. The set contains training and test sets. Both parts contain information about 100 engines.

Based on the data from the training set, it is necessary to predict the failure of the engine in the test set. RUL is expressed in number of cycles.

Sensors are sources of information about the condition of equipment components and assemblies and the operational conditions of the equipment.

The examples set is mean as DS. For each example $i \in DS$, multidimensional sensors data can be presented as time series $X^{(i)} = \{X_1^{(i)}, X_2^{(i)}, ... X_{T^{(i)}}^{(i)}\}$, where $T^{(i)}$ - length of time series for the i-th example, $X_t^{(i)} = \{x_{t,1}^{(i)}, x_{t,2}^{(i)}, ..., x_{t,n}^{(i)}\}$ - n-dimensional vector corresponding to the measurements of the n sensors at the moment of time t. For the i-th example of equipment for which a failure was fixed, the length $T^{(i)}$ corresponds to the full operational cycle (from initial state to failure), and for the current working example, the length $T^{(i)}$ corresponds to the expired time of exploitation (from the initial state to the current observed moment of time). For the system for which a failure was fixed, we can calculate the remaining resource RUL at each time step: $RUL(t_0) = t_1 - t_0$, if $t_1 \geq t_0$, where: t_1 - is the time at which the failure occurs (maximum time of system exploitation), t_0 - current time of observation for system work (Fig. 6). From here, a set of labeled data is generated. Based on these labeled data, models are formed for solving of task: the regression task is used to predict the value of the RUL of equipment. The resulting models can be used to develop recommendations for the optimal use of equipment. In this case, there are a set of characteristics of the system $X = \{X_1, X_2, \ldots, X_k\}$ and a set of possible answers $Y = \{y_1, y_2, \ldots, y_k\}$, which form a set of pairs $\{X_1, y_1), \ldots, (X_k, y_k)\}$.

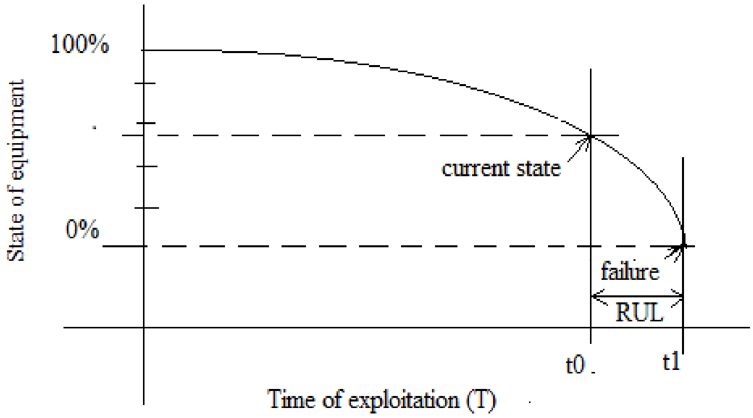


Figure 6. Dependence of equipment state from time

Based on this data, it is required to restore the dependence, to build a model able to determine the answer Y for any object X. For task of prediction $RUL^{(i)}$ of turbofan engines: there is required to find a function ϕ, such as

$R\hat{U}L_t^{(i)} = \phi(X_t^{(i)}, RUL_t^{(i)})$, to minimize error between predicted value of $R\hat{U}L^{(i)}$ and target value of $RUL^{(i)}$ at time t - minimize: $\{R\hat{U}L_t^{(i)}, RUL_t^{(i)}\}$.

The C-MAPSS data set contains four subsets of data (FD001-FD004) received from different time series. Each data subset consists of the test data set and a training data set, and the number of engines is different in each data subset. The engine works normal at the beginning of each time series and fails at the end of the time series. In the training set, the fault grows until the system fails and in the test set, the time series ends at some time before the system fails. In each time series, twenty one sensor parameters and three other parameters (operational setting) show the current state of the turbofan engine. Each row gives the data taken during a one operation cycle, and each column gives the data of one variable. The content of data set file is presented in Table 1.

Table 1. Content of data set file.

Number	Variable Name
1	unit number
2	time, in cycles
3	operational setting 1
4	operational setting 2
5	operational setting 3
6	sensor measurement 1
7	sensor measurement 2
8 …	…
26	sensor measurements 21

4.2. Data preprocessing and building of proposed deep neural networks

Data in FD001 data set in C-MAPSS dataset contains set of engine measurements from 21 sensors. For data set the collected data from sensors are normalized, using the min-max normalization method:

$$x_{norm}^{i,j} = \frac{2\left(x^{i,j} - x_{\min}^{j}\right)}{x_{\max}^{j} - x_{\min}^{j}} - 1, \forall i, j \tag{11}$$

where $x^{i,j}$ - i-th data value received from the j-th sensor, $x_{norm}^{i,j}$ - normalized data value of $x^{i,j}$, $x_{\max}^{i}$ and $x_{\min}^{j}$ - the maximum and minimum data values of the origin measurement data value received from the j-th sensor.

In this study a time window is used. The sensors data within the time window at each time step are used as input vector for the network. Time sequence process has a good potential for improving of prediction executing.

To receive the RUL of turbofan engines with great accuracy it was been proposed, built and used advanced models, which consist of several types of neural network models. It was been proposed, built and used such models:

1) LSTM model was built for RUL of turbofan engines prediction, which memorize information during long time periods. LSTM is the good instrument for model sequence data, in particular multiple time series,

2) hybrid CNN-LSTM model was built and used for RUL of turbofan engines prediction. CNN network is able to extract local information from data when convolutional filters slide on two-dimensional input data. The one-dimensional CNN was used for feature extraction. The extracted features were the input for LSTM network,

3) hybrid CNN-LSTM-encoder-decoder model was built and used for RUL of turbofan engines prediction. With the help of encoder the feature extraction about failure from data took place better. Clearing from noise occurs. The accuracy of prediction of turbofan engines RUL increased.

4) hybrid CNN-BLSTM model was built and used for RUL of turbofan engines prediction. The structure of BLSTM allows the network to receive information about the input sequence in the forward and backward direction of LSTM layer.

5) hybrid CNN-BGRU model was built and used for RUL of turbofan engines prediction. The structure of BGRU allows the network to receive information about the input sequence in the forward and backward direction of GRU layer. The accuracy of prediction of turbofan engines RUL of CNN-BGRU model higher than that for CNN-BLSTM model.

4.3. Evaluation metrics

In this study several popular metrics for evaluating the RUL prediction of turbofan engines are used: root mean square error (RMSE), mean absolute error (MAE), Score. They are calculated like this:

$$RMSE = \sqrt{\frac{1}{N}\sum_{1}^{N} Y_i^2} \quad (12)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |Y_i| \quad (13)$$

$$Score = \sum_{i=1}^{N} S_i \;, S_i = \begin{cases} e^{-\frac{Y_i}{13}} - 1, Y_i < 0 \\ e^{\frac{Y_i}{10}} - 1, Y_i \geq 0 \end{cases} \quad (14)$$

where Y_i - the difference between the predictive value of RUL and actual value of RUL of the i-th testing data sample, N- total number of testing data samples.

4.4. Results of experiments

The RUL prediction results by the various proposed models and the comparative analysis of the results were performed, results are presented below.

The RUL prediction results were obtained and compared, using LSTM, CNN-LSTM, CNN-LSTM-encoder-decoder, CNN-BLSTM, CNN-BGRU.

The hybrid CNN-LSTM model includes one-dimensional convolutional neural network (1DCNN) and LSTM network. Several 1DCNN layers precede LSTM layers. Time window was applied. In test data set each engine has different recorded data cycles. The shortest data cycle contain 31 cycles only. If a window length greater than 31 is used, the test engines, which have cycles shorter than 31, are removed from consideration. The kernel size of 1D convolution was chosen 3 with padding "same". The train data set of FD001 data set was applied for training of network models. Data from each sensors was preprocessed with min-max normalization method. We used early stopping and dropout to avoid overfitting. We tracked the loss on data set. If the loss on the data set does not decrease over 5 epochs, the training is stopped. We then take the best model that has the least loss on the data set. Dropout layers have been added to the network architecture, which filter out some of the blocks in the previous layer.

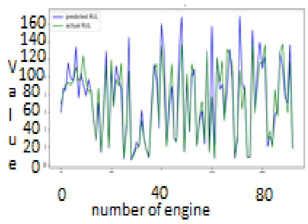
In the proposed hybrid CNN-LSTM-encoder-decoder model CNN used as the encoder, the decoding process is performed by LSTM-decoder. The CNN-encoder architecture contains two convolutional layers, max pooling layer, flatten layer, repeat vector layer. LSTM-decoder contains two LSTM-layers, Time distributed wrapper, dropout layers.

Proposed CNN-BLSTM and CNN-BGRU models are combinations of several convolutional layers and several BLSTM or BGRU layers respectively. Several 1DCNN layers precede BLSTM or BGRU layers. An input sequence is the input of one layer of BLSTM or BGRU in the forward direction, and the input of another layer in the backward direction. The outputs of the two layers are concatenated at each time step. This structure of the network allows to receive information about the input sequence in the forward and backward direction.

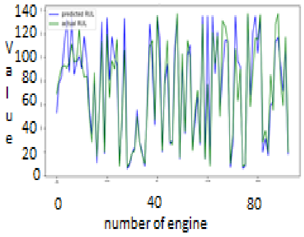
The training was carried out on the Google Colaboratory, with a GPU.

The prediction RUL of turbofan engine using proposed models were obtained. The RUL prediction results for test data set are shown in Fig. 7, where each number of the test engine corresponds to the RUL value, ground truth and predicted. In Fig. 7 you can see that when using models that contain convolutional layers, the errors in RUL prediction is significantly reduced – maximal value of predicted RUL reduced, what is nearer to ground truth of RUL.

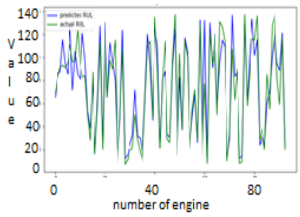
Comparison of the RMSE, MAE, Score for prediction results of RUL of turbofan engines on test set using proposed models with results of models proposed by other authors was presented in Table 2.



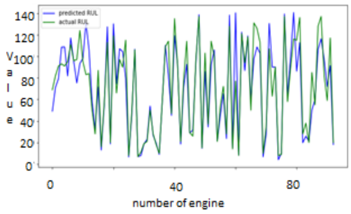
a) results of LSTM model



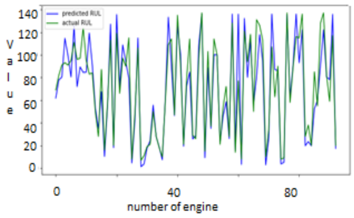
b) results of CNN-LSTM model



c) results of CNN-LSTM-encoder-decoder model



d) results of CNN-BLSTM model



e) results of CNN-BGRU model

Figure 7. RUL prediction results obtained with the help of different models

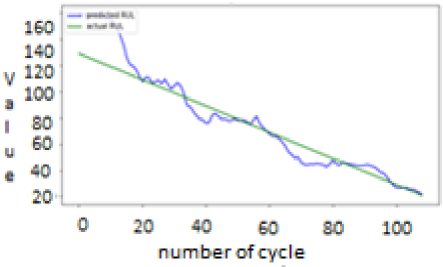
Table 2. RUL prediction results comparison with results of other models

Number	***Models***	***MAE***	***RMSE***	***Score***
1	MLP[22]	-	37.36	1800
2	SVR[22]	-	20.96	1380
3	CNN[22]	-	18.45	1290
4	LSTM	11.352	16.673	311
5	CNN-LSTM	10.399	14.987	279
6	CNN-LSTM-encoder-decoder	10.326	14.953	256
7	CNN-BLSTM	11.316	15.591	292
8	CNN-BGRU	11.277	15.497	286

Results in Table 2 shows that the lowest RMSE, MAE, Score value obtained using the CNN-LSTM-encoder-decoder model among the proposed models.

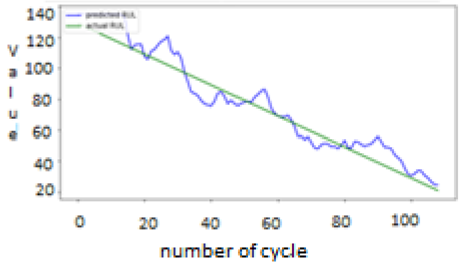
We also test the proposed models to predict the RUL of each engine in cycles, since we want to observe the process of its degradation. In Fig. 8 it is shown the RUL prediction results for engine # 61 in cycles, using different models.

RMSE=12.83



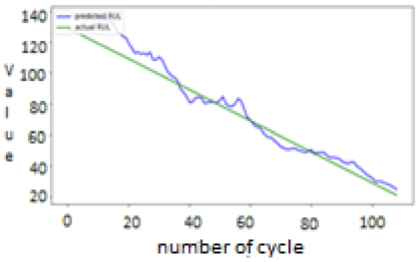
a) results of LSTM model

RMSE=8.79



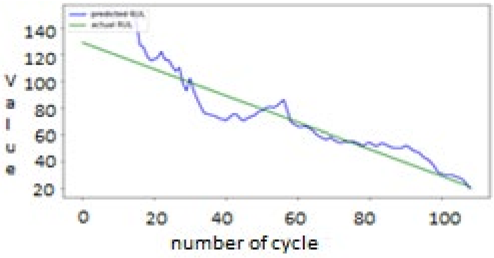
b) results of CNN-LSTM model

RMSE=7.78



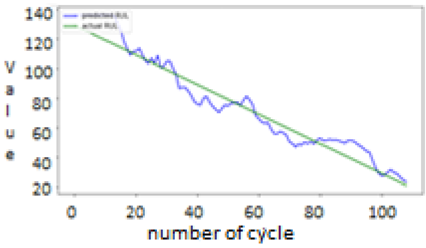
c) results of CNN-LSTM-encoder-decoder model

RMSE=11.76



d) results of CNN-BLSTM model

RMSE=8.05



e) results of CNN-BGRU model

Figure 8. RUL prediction results for engine # 61 in cycles, using different models.

It can be seen the degradation process of engine # 61 in cycles. Each figure shows trajectories of RUL: ground truth and predicted for each proposed models respectively. It can be seen from Fig. 8, a lowest RMSE value is observed when using the CNN-LSTM-encoder-decoder model. The accuracy of prediction of turbofan engines RUL of CNN-BGRU model higher than that for CNN-BLSTM model. Based on a comparison of the results obtained, we conclude that the CNN-LSTM-encoder-decoder model allows more accurately predict RUL of turbofan engine among the proposed models. The RMSE, Score of models, proposed in this study, shows that they are smaller than RMSE, Score of others models, what demonstrate the efficiency of proposed models.

5. CONCLUSION

In this study, new deep learning models for predicting RUL of turbofan engines are proposed, which based on CNN and LSTM models: LSTM, CNN-LSTM, CNN-LSTM-encoder-decoder, CNN-BLSTM, CNN-BGRU. To avoid overfitting dropout technique, early stopping are employed. The experiments were carried out on the C-MAPSS data set, which showed the effectiveness of proposed methods. Good results were obtained using data preprocessing, technique to avoid overfitting with proposed models. The RUL of turbofan engines was estimated with small errors. It was shown that lowest RMSE, MAE, Score values obtained using the CNN-LSTM-encoder-decoder model for predicting RUL of turbofan engines among the proposed models. The obtained results were compared with results of other researchers. The proposed network models have shown their efficiency, high accuracy, and the possibility of being used in industrial applications. Using these models will increase the reliability and safety of systems, and reduce maintenance costs. In future research, it is desirable to use these network models for other applications.

REFERENCES

[1] A. Azadeh, S. M. Asadzadeh, N. Salehi, M. Firoozi. Condition-based maintenance effectiveness for series-parallel power generation system - A combined Markovian simulation model. *Reliability Engineering and System Safety*, Elsevier, Vol. 142(C), 2015, pp. 357–368. DOI: 10.1016/j.ress.2015.04.009.

[2] Z. Zhao, L. Bin, X. Wang, W. Lu. Remaining useful life prediction of aircraft engine based on degradation pattern learning. *Reliability Engineering and System Safety*, Vol. 164(C), 2017, pp. 74–83. DOI: 10.1016/j.ress.2017.02.007

[3] J. Lee, F. Wu, W. Zhao, M. Ghaffari, L. Liao, D. Siegel. Prognostics and health management design for rotary machinery systems - Reviews, methodology and applications. *Mechanical Systems and Signal Processing*, Vol. 42, No. 12, 2014, pp. 314–334.DOI: 10.1016/j.ymssp.2013.06.004

[4] Y. Qian, R. Yan, R. X. Gao. A multi-time scale approach to remaining useful life prediction in rolling bearing. *Mechanical Systems and Signal Processing,* Vol. 83, 2017, pp. 549–567. DOI: 10.1016/j.ymssp.2016.06.031

[5] Huang Z., Xu Z., Wang W., Sun Y. Remaining useful life prediction for a nonlinear heterogeneous Wiener process model with an adaptive drift. Mathematics, Computer Science, *IEEE Transactions on Reliability*, Vol. 64, No. 2, 2015, pp. 687-700. DOI: 10.1109/TR.2015.2403433

[6] Liu J., Saxena A., Goebel K., Saha B., Wang W. An adaptive recurrent neural network for remaining useful life prediction of lithiumion batteries. *Annual Conference of the Prognostics and Health Management Society,* 2010, pp. 1-10.

[7] Lei Y., Li N., Gontarz S., Lin J., Radkowski S., Dybala S. A model-based method for remaining useful life prediction of machinery. *IEEE Transactions on Reliability*. 2016, pp. 1314-1326. DOI: 10.1109/ICPHM.2018.8448705

[8] Khoury E., Deloux E., Grall A., Berenguer C. On the use of time-limited information for maintenance decision support: A predictive approach under maintenance constraints. *Mathematical Problems in Engineering*, 2013, pp. 1-11. DOI: 10.1155/2013/983595

[9] De Benedetti M., Leonardi F., Messina F., Santoro C., Vasilakos A. Anomaly detection and predictive maintenance for photovoltaic systems. *Neurocomputing*. Vol. 310, 2018, pp. 59-68. https://doi.org/10.1016/j.neucom.2018.05.017

[10] A. Saxena and K. Goebel. "Turbofan engine degradation simulation data set", NASA Ames Prognostics Data Repository, 2008.

[11] J. Wei, P. Bai, D. Qin, T. Lim. Study on vbration characteristics of fan shaft of geared turbofan engine with sudden imbalance caused by blade off. *Journal of Vibration and Acoustics*, Vol. 140(4), 2018, pp. 1–14. DOI: 10.1115/1.4039246

[12] Tuzcu, H.; Sohret, Y.; Caliskan, H. Energy, environment and enviroeconomic analyses and assessments of the turbofan engine used in aviation industry. *Environmental Progress & Sustainable Energy*, Vol. 3, 2020, pp, 135-147. https://doi.org/10.1002/ep.13547

[13] Yakovleva, Ek.; Erofeev. P. Data-driven models for run-to-failure time prediction for aircraft engines. *Information Technologies and Systems*, 2015, pp. 287 -294.

[14] Ellefsen, A.L., Bjorlykhaug E., Æsøy V., Ushakov S., and Zhang H. Remaining useful life predictions for turbofan engine degradation using semi-supervised deep architecture, *Reliability Engeneering and System Safety*, Vol. 183, 2019, pp. 240–251. DOI: 10.1016/j.ress.2018.11.027

[15] Ordóñez Galan C., Sanchez Lasheras F., Roca Pardiñas J., Cos Juez F. J. A hybrid ARIMA–SVM model for the study of the remaining useful life of aircraft engines. *Journal of Computational and Applied Mathematics*, Vol. 346, 2019, pp. 184–191. https://doi.org/10.1016/j.cam.2018.07.008

[16] Peng, C., Tang, Z., Gui, W. Review of key technologies and progress in industrial equipment health management. *IEEEAccess,* Vol. 8, 2020, pp. 151764–151776.

[17] Yang, B., Liu, R., Zio, E. Remaining useful life prediction based on a double-convolutional neural network architecture. *IEEE Transactions on Industrial Electronics*, Vol. 66, № 12, 2019, pp. 9521–9530. DOI: 10.1109/TIE.2019.2924605

[18] Hsu, H., Srivastava, G., Wu, H., Chen, M. Remaining useful life prediction based on state assessment using edge computing on deep learning. *Computer Communications*, Vol. 160, 2020, pp. 91–100. DOI: 10.1016/j.com.2020.05.035

[19]Li, X., Ding, Q., Sun, J. Q. Remaining useful life estimation in prognostics using deep convolutional neural networks. *Reliability Engineering and System Safety,* Vol. 172(C), 2018, pp. 1–11. DOI: 10.1016/j.ress.2017.11.021

[20] Zhang J., Wang P., Yan R., Gao R. Long short-term memory for machine remaining life prediction. *Journal of Manufacturing Systems*, Vol. 48, 2018, pp. 78–86. DOI:10.1016/j.jmsy.2018.05.011

[21]. Song, Y., Shi G., Chen L., Huang X., Xia T. Remaining useful life prediction of turbofan engine using hybrid model based on autoencoder and bidirectional long short-term memory. *Journal of Shanghai Jiaotong University*, Vol. 23, 2018, pp. 85-94. DOI: 10.1007/s12204-018-2027-5

[22] Babu G., Zhao P. and Xiao-Li L. Deep convolutional neural network based regression approach for estimation of remaining useful life. *Database Systems for Advanced Applications*, 2016, pp. 214-228. DOI: 10.1007/978-3-319-32025-0 14

Information about the authors:

Katerina M. GRITSYUK, Ph.D., National Technical University “Kharkiv Polytechnic Institute”, Kharkiv, Ukraine. She is lecturer and researcher. Her scientific interests include: regression analysis, artificial intelligence, knowledge-based systems, machine learning, prediction of different indices.

Vera I. GRITSYUK, Ph.D., Associate Professor. Kharkiv Institute of State University of Telecommunications, Ukraine. Number of publications in Ukrainian editions is 47 and number in foreign indexed editions is 10. Her scientific interests include: regression analysis, modeling, prediction, stochastic control systems.

Manuscript received on 06 January 2022