PREDICTION OF REMAINING USEFUL LIFE WITH HELP OF DEEP LEARNING MODELS WITH REGULARIZATION

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Abstract: Nowadays the use of modern technologies leads to an increase in the complexity of equipment. Failures of equipment lead to enterprises shutdowns or breakdowns not at enterprises. In this regard, there is a need to predict the remaining useful life of equipment with great accuracy in order to replace its parts at a time close to the time of its failures. This increase safety and reliability and reducing maintenance costs. Predictive maintenance of equipment is replacing corrective and preventive maintenance. In this study to improve prediction accuracy of remaining useful life of equipment it is proposed deep learning models using convolutional and long short-term memory neural networks. To solve the problem of overfitting of the neural networks during the training process, the regularization entered into their structures. Experimental results on real data show that the proposed methods can achieve higher stability and accuracy, which are useful for prediction of remaining useful life of aero engines and have high efficiency.

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

1. INTRODUCTION

Maintenance of equipment and prognostics are important at all industrial enterprises. Intelligent prognostic and health management (PHM) are important everywhere in industry [1]. Corrective and preventive maintenance [2] are not always necessary since there are cases of “premature” sending of equipment for repair when the equipment resource is not exhausted and reliable information about the condition of the equipment is not taken into account.

The following strategy is becoming popular. Change in voltage, temperature going beyond threshold values, extraneous sound in the engine recorded by monitoring and control systems of technological processes in the operation of machines or devices. Based on sensor information, the equipment condition is analysed, and a prediction is made regarding the development of the situation. Predictive maintenance (PdM) is the maintenance and repair of equipment based on the real condition of the equipment, when there is a prediction for breakdown, without reference to regulatory and technical documentation or production instructions. PdM is the process of managing equipment at an enterprise, which includes collecting and analyzing information about the state of equipment and making a prediction about the time of equipment failure in order to prepare and implement measures to prevent operational failures.

PdM eliminates the need to interrupt production processes because it helps recognize even small changes in equipment condition that would not be detected during a typical inspection. Artificial intelligence tools allow manufacturers to identify conditions that can cause breakdowns and intervene before they occur.

In this regard, it becomes important to predict the remaining useful life (RUL) of equipment. Historical data are used in prediction of RUL. Processing a large amount of sensor data, determining the actual state of the system and predicting its future states using machine learning (deep learning) approaches is the PdM strategy in the industry 4.0 concept. Using machine learning models, manufacturers can predict the remaining life of equipment and prepare for repairs. Reliable RUL predictions helps in the following: minimize the risk of accidents in the context of the need to maintain uninterrupted operation of equipment; save money on preventative maintenance by reducing cases of "premature" removal of equipment for repair; plan costs for the purchase of spare parts, repairs and maintenance; removal of equipment beyond repair.

In this study are proposed efficient deep learning models for prediction RUL of aircraft engine.

The purpose of this study: select data set and performing data preprocessing; using combinations of convolutional neural network (CNN) and a long short-term memory network (LSTM) build deep learning models with regularization entered into network structures to increase accuracy of RUL prediction; evaluate results obtained using models with the RMSE, MAE and Score metrics.

In this study to improve the solution of the problem of overfitting of neural networks during the training process, increasing the accuracy of predictions, the regularization is entered into the structure of the networks. When comparing the prediction results, it was found that neural networks with entered regularization predict results with greater accuracy.

2. BASIC METHODS, MODELS FOR RUL PREDICTION

Data-driven, model-based and hybrid methods are used for PdM.

Historical data of sensors are used in data-driven methods for system state modelling.

It is possible to discover underlying correlations in sensor data and obtain RUL information. These methods abstract from the physical nature of objects and therefore have universal properties. Data-driven methods are actively used. In PdM the artificial neural networks for prediction RUL of equipment are applied.

If the degradation of the system can be accurately modeled and there is general knowledge about the physical system, model-based methods are used.

Data-driven and model-based methods have shown benefits in a variety of applications. Obtaining actual fault data is difficult task because it is time consuming and expensive. NASA proposed the commercial modular aero-propulsion system simulation (C-MAPSS) dataset that is used for estimating the RUL of aircraft engines. The basis of the aircraft - turbofan engines, which is very complex and expensive equipment. Most aircraft malfunctions are related to turbofan engines. PdM of aircraft is based on prediction of RUL of turbofan engines. Deep learning models and its using help improve efficiency of turbofan engines.

CNN are widely used in prediction of RUL. Their great potential in feature extraction is known.

LSTM the type of recurrent neural network (RNN). The LSTM cell has a three-gate structure. This allows work with time series data. To predict the RUL the LSTM processes time series data.

Hybrid models that combine several neural network models are proposed in this study, and regularization is included in these models.

3. STRUCTURES OF NETWORKS, SUGGESTED IN RESEARCH

In suggested method RUL prediction is based on an array of historical data. The architecture that implements PdM approach is presented in Fig. 1. Based on the data, models are formed which help to obtain numerical values of the predicted RUL of equipment. The resulting models can be used to develop recommendations for the optimal use of equipment online.

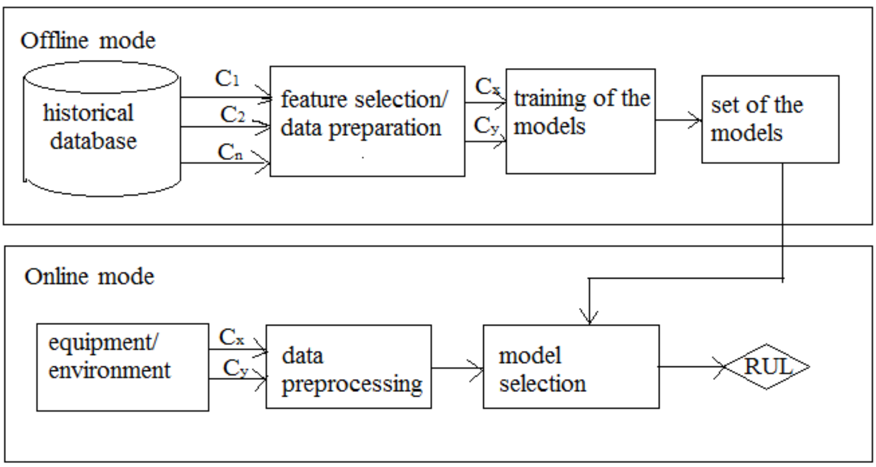


Fig. 1. Predictive maintenance system architecture

PdM helps reduce the risks associated with unexpected failures and eliminate unnecessary costs. In PdM strategy processing a large amount of sensor data, prediction of RUL of equipment carry out using machine learning (deep learning) approaches.

To improve the quality of RUL prediction, in this study is proposed hybrid neural network models with regularization. It is proposed several combinations of CNN and LSTM networks for predictions of RUL with the entering of L2 regularization in models.

CNN is one of architectures of artificial neural networks. They are often used for image and video processing. They extract information from data with high ability due to convolutional filters slide on two-dimensional input data. The collected sensor data are similar to two-dimensional data. That is why CNN is used to solve these problems.

Structure of LSTM is more complex, than RNN, although they contain repeating modules too. Input gate, forget gate, output gate – special layers of LSTM cell.

In Fig. 2 the structure of the LSTM network fragment is shown, where M - LSTM cell. The property of LSTM cells is to remember received information for long time periods. Modeling of multivariate time series data well carried out with the help of LSTM network.

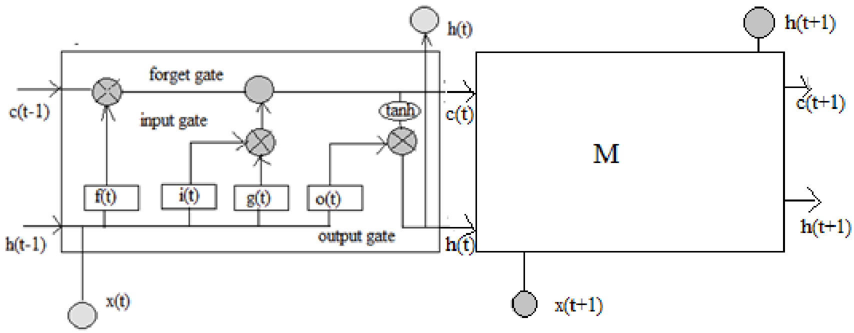


Fig. 2. Structure of LSTM network fragment

I(t), the input gate, controls what information will be transferred to the memory cell. The f(t), forget gate, controls how the cell is updated. o(t), output gate, controls which information will be transferred to next time step.

Since any model has its limitations and disadvantages when predicting RUL, to solve this problem use a combination of different models to improve forecasting accuracy. In this study, a hybrid CNN and LSTM models are proposed which achieves good results in prediction of the RUL of turbofan engines. We use the CNN layers before the LSTM-layers because we have measurements from many sensors. CNN is used to extract features and LSTM is used to interpret functions at time steps. The regression model is trained by a deep neural network (DNN).

In Fig. 3 the architecture of proposed CNN-LSTM model for RUL prediction of turbofan engines with regularization, where one CNN and LSTM layer, r - schematic representation of the regularization component, is shown.

In this study also proposed and created the CNN-Bidirectional LSTM (CNN-BLSTM), CNN-Bidirectional Gated Recurrent Unit (CNN-BGRU) models with regularization.

The GRU cell contains reset gates r(t) and update gates z(t). The reset gate r(t) determines the combination of the new input with the previous memory. The update gate z(t) defines the quantity of memory information to determine the new state.

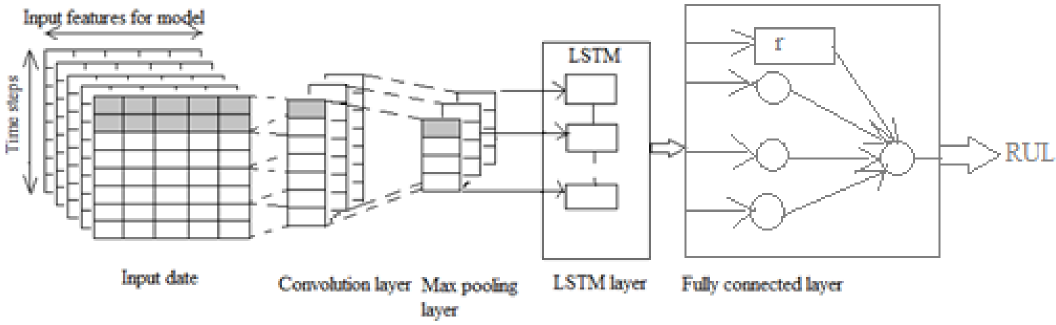


Fig. 3. Architecture of CNN-LSTM model for RUL prediction

BLSTM, BGRU models contains two LSTM, GRU layers respectively. One of these two layers processes input information in one of the directions - forward or backward and then outputs of layers are combine. This increases the available information for the network.

To avoid overfitting of these models, improve the accuracy of RUL prediction results we applied L2 regularization or Ridge regression. L2 regularization adds a penalty. This penalty helps lower the weights, resulting in a more robust model. The error function in a task with L2 regularization has the form below; a regularization term is added to the error function:

$$Loss = \sum_{i=1}^{n}\left(y_i - \sum_{j=1}^{p} x_{ij}\hat{\beta}_j\right)^2 + \lambda \sum_{j=1}^{p} \hat{\beta}_j^2 \quad (1)$$

where λ - hyperparameter, y_i - target data value, $\hat{\beta}_j$ - estimates of coefficients, $\hat{y}_j = \sum_{j=1}^{p} x_{ij}\hat{\beta}_j$ – predicted data value.

Each of the proposed network models was used with the entered regularization.

4. EXPERIMENTS AND RESULTS

4.1. Dataset, data preprocessing and creating of models of deep neural networks for RUL prediction

C-MAPSS data set contains four data subsets. Data subsets contain information from 21 sensors simulating engines state and from 3 sensors- about the state of the systems. Each of the four data subsets FD001-FD004 of C-MAPSS dataset contains a test data set and a training data set. The number of engines in each data subsets is different.

The FD001 data subset was chosen to demonstrate efficiency of suggested models. This data subset contains training and test sets with 100 trajectories.

Information from n sensors at moment of time t let us denote as $X_t^{(i)} = \left\{x_{t,1}^{(i)}, x_{t,2}^{(i)}, \ldots, x_{t,n}^{(i)}\right\}$

from n sensors for each i are time series $X^{(i)} = \{X_1^{(i)}, X_2^{(i)}, ... X_{T^{(i)}}^{(i)}\}$, where T_i corresponds to a time from initial state to current moment or to time of failure, if it occurred.

If failure in the system was recorded in moment t_1 and current time t_0, $t_0 \leq t_1$, then we calculate remaining resourse RUL like this: $RUL(t_0) = t_1 - t_0$ (Fig. 4). The prediction of the equipment RUL done when solving the regression task.

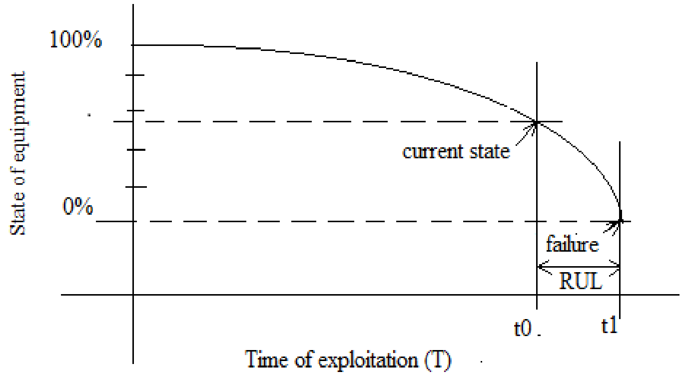


Fig. 4. Dependence of equipment state from time

There are a set of system characteristics $X = \{X_1, X_2, ... X_k\}$ and a set of answers $Y = \{y_1, y_2, ..., y_k\}$, from which pairs are formed $\{X_1, y_1), ..., (X_k, y_k)\}$. A task appears: it is necessary to build a model that for any object X will find answer Y. In this task it is necessary to define a function φ, $R\hat{U}L_t^{(i)} = \varphi(X_t^{(i)}, RUL_t^{(i)})$, that will minimize value of $R\hat{U}L^{(i)}$ - $RUL^{(i)}$ at time *t*.

Min-max normalization is used to normalize sensors data from the FD001 subset:

A time window was used in this study. The time sequencing process helps improve the prediction process.

Improved models containing several types of neural networks models with regularization were proposed, constructed, and used to obtain the RUL of turbofan engine with great accuracy. The following models were proposed, created and used:

1) LSTM model;
2) CNN-LSTM model;
3) CNN-BLSTM model;
4) CNN-BGRU model;

To avoid overfitting of these models and improve the accuracy of RUL prediction, we applied L2 regularization for each of the proposed models.

4.2. Evaluation of RUL prediction results

Results of RUL prediction of turbofan engines using proposed models are evaluated applying the following metrics: root mean square error (RMSE), mean absolute error (MAE), Score. The following formulas are used:

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

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |Y_i| \quad (3)$$

$$Score = \sum_{i=1}^{N} S_i \ , S_i = \begin{cases} e^{-\frac{Y_i}{13}} - 1, Y_i < 0 \\ e^{\frac{Y_i}{10}} - 1, Y_i \geq 0 \end{cases} \quad (4)$$

where $Y_i = R\hat{U}L_i - RUL_i$, i – number of data example, N- total number of data examples.

4.3. Experiments results

All proposed models were created and used to predict RUL, and a comparative analysis was carried out. These results of predictions are compared with results of predictions using LSTM, CNN-LSTM, CNN-BLSTM, CNN-BGRU without introducing a regularization term.

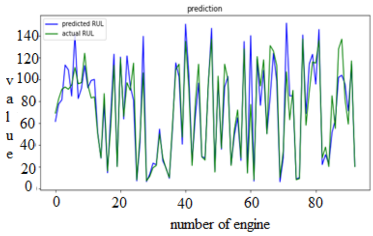
In the CNN-LSTM model: some 1DCNN layers, and then some LSTM layers were used. A time window has been used. 3 - selected size of the 1D convolution kernel with "same" padding. To train the network models the train dataset from dataset FD001 was used. Min-max normalization was used to preprocess data. Early stopping and dropout technic were used to avoid overfitting. Training stops if the loss on the dataset does not decrease over 6 epochs. The best model that had least losses on the dataset was selected. Removing some components of the previous layer is done by adding dropout layers to the network.

In CNN-BLSTM and CNN-BGRU models: some 1DCNN layers, then some BLSTM or BGRU layers were used. One of the two layers LSTM or GRU in BLSTM or BGRU models respectively processes input information in one of the directions - forward or backward and then outputs of layers are combine.

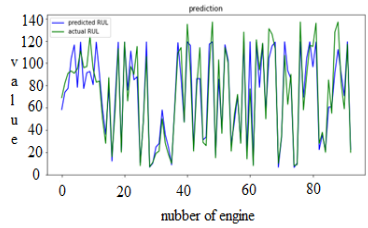
Each model was used to predict RUL with L2 regularization. It was found that the use of L2 regularization increased the accuracy of RUL prediction of turbofan engines for all proposed models and increase the robustness of models.

GPU in Google Colaboratory was used for training of the networks models.

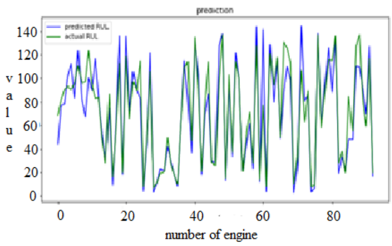
The RUL prediction of a turbofan engines was obtained using the proposed models. The results of RUL prediction for the test data set with the introduction of L2 regularization are shown in Fig. 5. For each engine number of the test set the predicted and target value of RUL are shown. In table 1 the comparison of the results of RMSE, MAE, Score for the evaluating of predicting RUL of turbofan engines for the proposed models without [3] and with the entering of L2 regularization into the models is presented.



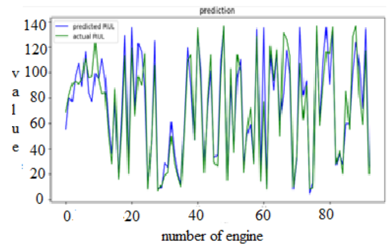
a) RUL obtained with LSTM model and target value



b) RUL obtained with CNN-LSTM model and target value



c) RUL obtained with CNN-BLSTM model and target value



d) RUL obtained with CNN-BGRU model and target value

Fig. 5. Prediction of RUL with the help of different models with regularization

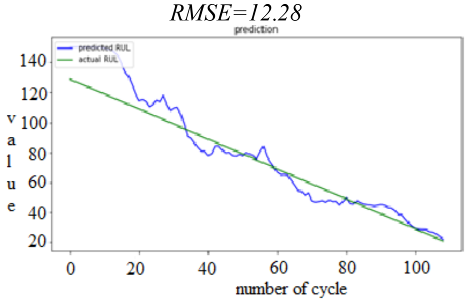
Table 1. Results of RUL prediction without and with regularization

Number	***Models***	***MAE***	***RMSE***	***Score***
1	LSTM	11.352	16.673	311
2	LSTM with regularization	10.319	15.361	239
3	CNN-LSTM	10.399	14.98	279
4	CNN-LSTM with regularization	10.246	13.96	178
5	CNN-BLSTM	11.316	15.591	292
6	CNN-BLSTM with regularization	10.736	15.475	258
7	CNN-BGRU	11.277	15.497	286
8	CNN-BGRU with regularization	10.895	14.781	209

As we can see from here the lowest RMSE, MAE, Score among the proposed models is obtained using CNN-LSTM model with regularization. We also see that the entering of regularization increased the accuracy of RUL prediction for all proposed models.

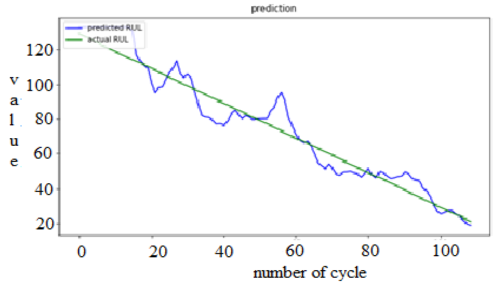
We would like to observe the degradation process of each engine, so we predicted the RUL for it. The results of RUL prediction for engine No. 61 are shown in Fig. 6, where all proposed models with regularization are used.

RMSE=12.28



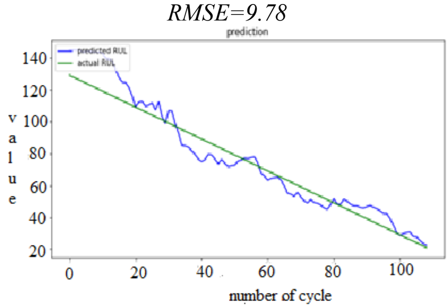
a) RUL obtained with LSTM model and target value

RMSE=8.16



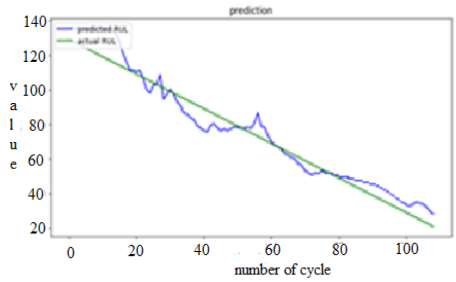
b) RUL obtained with CNN-LSTM model and target value

RMSE=9.78



c) RUL obtained with CNN-BLSTM model and target value

RMSE=8.21



d) RUL obtained with CNN-BGRU model and target value

Fig. 6. Prediction of RUL for engine # 61 with different models with regularization

The wear process of engine No. 61 is presented in Fig. 6. The predicted and target RUL value trajectories are shown in each figure for one of proposed models. Using the CNN-LSTM model allows us to obtain the lowest RMSE value. Using of the CNN-BGRU model allows us to obtain the RUL of turbofan engines with higher accuracy then using of CNN-BLSTM model. Evaluation of the proposed models by RMSE, SCORE shows that entering of regularization into neural network models improves the prediction accuracy of RUL of turbofan engines. This demonstrates the effectiveness of the proposed models with entering of regularization into the models.

5. CONCLUSION

Deep learning models LSTM, CNN-LSTM, CNN-BLSTM, CNN-BGRU with entering of regularization into these models to reduce overfitting and improve the accuracy of RUL of turbofan engines prediction are created and used. L2 regularization adds a penalty that helps lower the weights, resulting in a more robust model.

The dropout technique, early stopping were also used to avoid overfitting. The effectiveness of the proposed models was demonstrated when C-MAPS dataset was used. Preprocessing of input data was performed. RMSE, MAE and SCORE values using proposed models with regularization have decreased.

Among the proposed models using of CNN-LSTM model with regularization for predicting RUL of turbofan engines gives lowest value of RMSE, MAE, Score. It is also shown that the entering of the regularization into the neural network models increased the accuracy of the RUL prediction for all proposed models.

It was found that the proposed network models make it possible to obtain predicted results of RUL with great accuracy and efficiency, which are improved by entering a regularization into the models.

The process of RUL prediction can significantly improve all stages of maintenance of equipment, reduce maintenance costs and increase safety and reliability of systems. Therefore, it is very important to improve the accuracy of RUL prediction with help of deep learning network models, to avoid overfitting problem by entering regularization into models and other.

Future work will include research the use of regularization and other methods to improve the accuracy of RUL predictions and thereby increasing reliability, durability and efficiency of systems.

REFERENCES

[1] H. Gharib, G. Kovacs. A Review of Prognostic and Health Management (PHM) Methods and limitations for marine diesel engines: New research directions. *Machines,* vol. 11, no.7, 2023, p.22. DOI: 10.390/machines11070695.

[2] M. Moleda, B. Malysiak-Mrozek, V.Sunderam, D. Mrozek. From corrective to predictive maintenance – a review of maintenance approaches for the power industry. *Sensors (Basel)*, vol.23, no.13, 2023. DOI: 10.3390/s23135970.

[3] Gritsyuk K, Gritsyuk V. Convolutional and long short-term memory neural networks-based models for remaining useful life prediction. *International Journal on Information Technologies & Security*. vol.14, no.1, 2022, pp.61-76.

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