Diagnostic signal nonstationarity reduction to predict the helicopter transmission state on the basis of intelligent information technologies

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Abstract. Analysis process and transformation of non-stationary diagnostic signals to reduce the degree of their non-stationarity and the subsequent synthesis of neural network predictive model based on them are considered. The software which allows to apply the developed methods for processing of signals of diagnostics of transmission of the helicopter and on their basis to build the forecasting model for the solution of practical problems of technical diagnostics is developed.

Keywords: nonstationary signal, diagnosis, Dickey - Fuller criterion, neural network, dimension reduction

1 Introduction

Preventing machinery failure is an important component of the maintenance activities of most engineering systems. For quality control of a technical product, at the end of its production and during design tests technical diagnostics is carried out.

Automation of decision-making in the process of technical diagnosis is an urgent task, as it helps to reduce the load on the human operator, as well as provides efficiency and speed of decision-making and reduces the dependence of complex technical systems on the negative impact of the human factor.

A promising basis for solving the problems of automation of diagnosis are intelligent information technologies that are able to build models for examples – experimental observations "input - output" and extract knowledge from the data in the learning process.

The paper considers the process of diagnosing the helicopter transmission. The helicopter is a complex and valuable technical product. Therefore, after designing the test sample is tested on the stand for a large number of hours. During these tests, changes in the vibration level of the sample are monitored. As a result of such tests, a large amount of data is accumulated in the form of diagnostic signals.

A sharp increase in vibration negatively affects the sample, which can lead to its failure. This entails material costs and the need to suspend testing. Therefore, having a system that can predict the vibration level for a certain time in advance will help to improve the testing process.

The basis of such a system can be used an intelligent model of data-driven [1, 2], for example, as one of the most powerful ones - the neural network model, by teaching it to predict the future level of vibration based on historical data collected. However, incoming signals are characterized by a high degree of non-stationary, which makes complex and long-time synthesis and training of such models.

The goal of the work is to develop methods for converting diagnostic signals to reduce their dimension, allocating the necessary component and reducing the degree of their non-stationary for further synthesis of neuromodels based on them.

The objective of this study is to predict these signals using neural network models.

2 Formal problem statement

Consider the problem of diagnosing the helicopter transmission [4]. Preventing machinery failure is an important component of the maintenance activities of most engineering systems. Helicopters are constantly exposed to periodic loads and vibrations that initiate and propagate the occurrence of damage in many components of the equipment. This is due to the design of the helicopter and the presence of complex mechanical systems, such as the inventive rotor, control rotor, main gearbox and other transmission elements. In most cases, the failure of these systems lead to catastrophic situations.

For monitoring the technical condition of the helicopter used systems like Health and Usage Monitoring Systems (HUMS) [5-6]. These systems make it possible to detect damage in the transmission components and predict their residual life.

Important in HUMS is the ability to assess the technical condition of critical elements of the transmission, using the data of vibration signals that were recorded during the flight or ground tests.

A neural network model will be used as a predictive model. Formally, the problem of neuromodels synthesis can be presented in this form.

Suppose given the original sample as a set of prece-dents (instances) $\langle x_t, y_t \rangle$ is a set of S precedents characterizing dependence $y_t(x_t)$, at the moment t, t = 1, 2, …, T, where $x_t=\{x^s_t\}$, $y=\{y^s_t\}$, s = 1, 2, ..., S, characterized by the set of N input features $\{x^t_j\}$, j = 1, 2, ..., N, where j is a number of feature, and output feature y. Each s-th precedent can be noted as $\langle x^s_t, y^s_t \rangle$, where $x^s_t=\{x^s_{tj}\}$.

Then the problem of model synthesis of dependence $y_t(x_t)$ will be considered in search of such structure $F()$ and adjusting such values of parameters w of a model which will satisfy the model quality criterion $f(F(), w, \langle x_t, y_t \rangle) \rightarrow opt$, where opt – is a symbol of optimum. Usually, the criterion of learning quality of neuromodels is defined as a function of model error (1):

$$E = \frac{1}{2}\sum_{s=1}^{S}(y^5 - F(\omega, x^5))^2 \to \min. \quad (1)$$

3 Analysis of the level of nonstationarity of the signals of the diagnostic process

In most research methods, it is assumed that the signal, and in General, any time series is stationary, and the time dependence is considered possible to take into account a variety of non-statistical methods. For example, the series is decomposed into three components: trend, cyclic and random. A trend is a component of a series that changes over a long period of time due to the influence of fundamental factors. The cyclic component changes in time with a certain period according to the course of repetitive processes. The random component includes all the last components that can not be assigned to one of the first two groups. The use of such separation for technical diagnostic signals may not provide optimum results due to the following factors.

First, the component can be quite complicated. For example, its trend characteristics may be nonlinear and non-linear, as predicted in most trend allocation methods. Secondly, in the tasks of technical diagnostics there is always a "white noise", the smallest error of forecasting which is equal to its dispersion. Thus, the series is divided into three parts, although this separation is fuzzy, the cyclic component can become a trend at intervals of less than a period, and the trend and the cyclic component can go into the category of random component.

The solution of the problem of stationary signaling of technical diagnostics is possible, but in most cases it entails a significant change in the structure of the signal itself. And the evaluation of the technical product on the received signal can not provide the necessary level of its quality. Metrics that are based on the components of its internal structure, for example, based on its wavelet decomposition [11], can be applied to a non-stationary signal to assess the quality of a technical product on a diagnostic signal. However, before switching to the application of such methods of constructing forecasting models, it is necessary to make sure that all possible procedures have been carried out to minimize the unsteadiness of the series, which does not lead to a significant change in its initial structure.

To estimate the degree of unsteadiness of the signal, we will use the dilated Dickey-Fuller criterion [13], the number of shifts will be calculated based on the data minimization of the information criterion (AIC - metric). This criterion is used to test the hypothesis of stationarity of the time series. Also, this criterion can be used to estimate the degree of nonstationarity of the time series. The closer the criterion value to the boundary, the lower the degree of nonstationarity has the signal. The values of the Dickie-Fuller criteria for the obtained values are given in Table 1.

Table 1. The value of the Dickie-Fuller criterion for processed signals.

Name of the transmission element	Place of measurement of the input signal	Direction of measurement	Controlled parameter	Value of the extended Dickey-Fuller criterion	Critical value of the extended Dickey-Fuller criterion (for Mac Kinnon [14]) for *p* = 0.95
Rotor blade	Rotor shaft cover	Vertical	Vibration speed	-8.37	-2.86
First gear drive of the intermediate gearbox	Intermediate gearbox	Horizontal	Vibration overload	-9.76	-2.86
		Axial	Vibration overload	-10.44	-2.86
First gear drive of the tail gearbox	Tail gearbox	Vertical	Vibration overload	-13.55	-2.86
		Axial	Vibration overload	-9.29	-2.86

From the results it is possible to observe a sufficiently high degree of unsteadiness of the studied signals. To find the relationship between the current and the previous signal values, we use the auto-correlation function. Autocorrelation is a correlation of the function itself with a certain variable of an independent variable. The autocorrelation function is defined as:

$$R_f(\tau) = \int_{-\infty}^{+\infty} f(t) f^*(t-\tau) dt, \qquad (2)$$

where the function $f(t)$ integrates into a product with a complex conjugate and a function displaced by a certain value τ .

The graph of the signal received on the intermediate gearbox (axial direction of measurement), which characterizes the state of the first gear drive of the intermediate gearbox is shown in Fig. 1. The graph also contains a 95% confidence interval to determine the statistical significance of the autocorrelation coefficient.

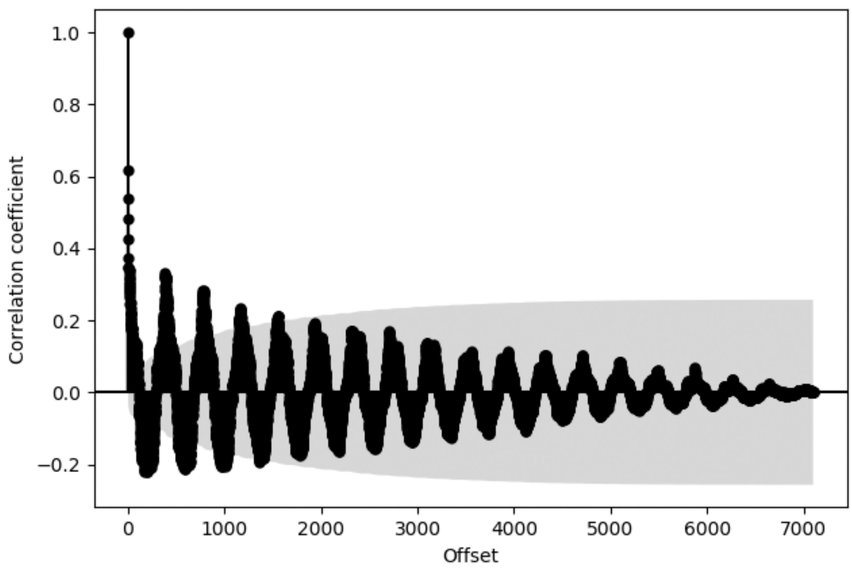

Fig. 1. Autocorrelogram of signal received on the intermediate gearbox (axial direction of measurement)

The carried autocorrelation analysis confirmed the proposed assumption of the presence of cyclicity in the signal. The presence of auto-correlation complicates the use of a number of methods of analysis of time series. Therefore, to reduce autocorrelation, elimination is used to shift from correlation of levels to correction of deviations from trends - residues (for example, the conversion of a time series into a number of values of differences between its adjacent members). This approach can not be applied in this case due to the above reasons for impossibility to change the initial structure of the diagnostic signal.

Another solution to this problem is to split the signal into several components, which will eliminate cyclicity and maintain the original signal strength.

4 Reduction of the nonstationarity of the signals based on information about the operating modes in the cycle of diagnosis

To reduce the non-stationary time series, methods can be applied that will lead to its breakdown into a certain number of smaller time series, in such a way that they are absent, explicitly, as a component of cyclicity [12]. When applying such a breakdown, the problem is to find the period of the cycle (which can change over time). For qualitative partitioning of a series it is necessary to use knowledge of the subject area of the investigated process. Apply expert knowledge in the field of aircraft engineering for breaking the signal of diagnosis. Fig. 2 shows a graph of signal of rotation of the turbocharger rotor left engine.

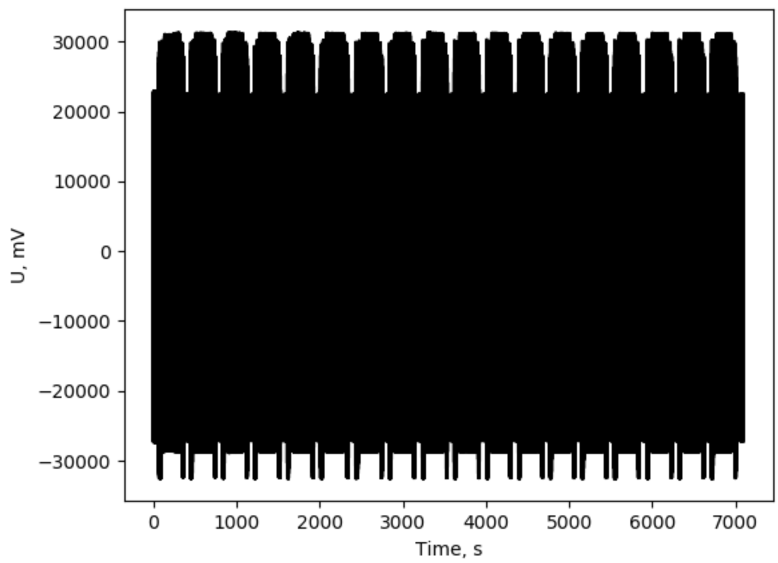

Fig. 2. Raw signal of rotation of the turbocharger rotor left engine

We process the processing of these signals to obtain the values of the rotational frequency by counting the number of times the signal changes in 1 second (the discretization frequency of the rough signal 7200 Hz). The graph of the signal received on the intermediate gearbox (axial direction of measurement), which characterizes the state of the first gear drive of the intermediate gearbox is shown in Fig. 3.

Fig. 3. Processed signal of rotation of the turbocharger rotor left engine

After processing the signal, you can observe the progress of 18 cycles of diagnosis. You can also observe the change in operating modes. In one mode of operation, the speed does not change significantly. The processed signals of rotation of the turbocharger rotor right engine demonstrate similar results. This is because the left and right engines duplicate each other to increase reliability.

It is proposed to allocate from the general signal of diagnosing the intervals during which the diagnosis took place in one mode of operation. For example, we isolate from the general signal for diagnosing the intervals during which the diagnosis took place in the second mode of operation. It is proposed to perform autocorrelation analysis for the received signals.

The graph of the signal received on the intermediate gearbox (axial direction of measurement), which characterizes the state of the first gear drive of the intermediate gearbox in the second mode of operation of turbochargers is shown in Fig. 4 The graph also contains a 95% confidence interval to determine the statistical significance of the autocorrelation coefficient.

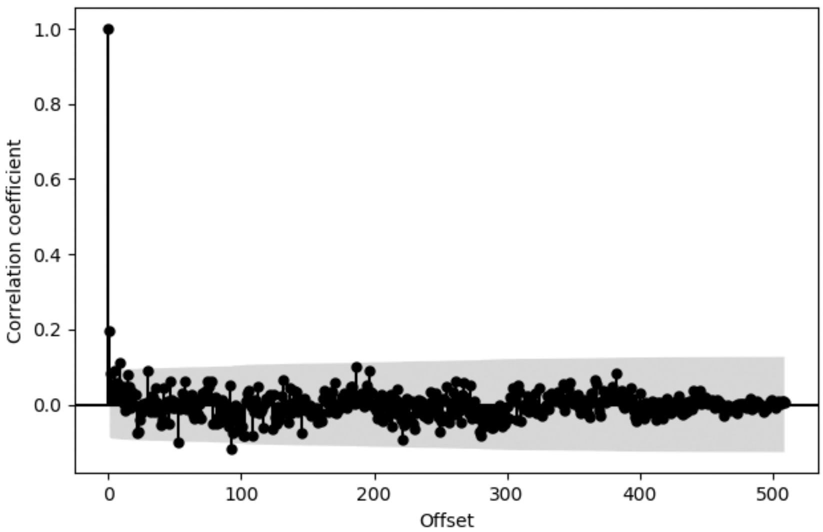

Fig. 4. Autocorrelogram of signal received on the intermediate gearbox (axial direction of measurement) in the second mode of operation of turbochargers

The performed autocorrelation analysis demonstrates the absence of expressed cyclicity in the signal. This indicates a qualitative breakdown of diagnostic signals, which should help to reduce the unsteadiness of newly formed signals.

To quantify the degree of non-stationarity of the signals, we calculate the values of the Dickey - Fuller criterion for them. Table 2 contains the values of the extended Dickey - Fuller criterion for part of the signals obtained from the signals of diagnosing the helicopter transmission by the proposed methods gearbox in the second mode of operation of turbochargers.

Table 2. The values of the extended Dickey - Fuller criterion for the signals obtained from the signals of diagnosing the helicopter transmission in the second mode of operation of turbochargers.

Name of the transmission element	**Place of measurement of the input signal**	**Direction of measurement**	**Controlled parameter**	**Value of the extended Dickey-Fuller criterion**	**Critical value of the extended Dickey-Fuller criterion (for Mac Kinnon [14]) for *p* = 0.95**
Rotor blade	Rotor shaft cover	Vertical	Vibration speed	-5.42	-2.86
First gear drive of the intermediate gearbox	Intermediate gearbox	Horizontal	Vibration overload	-5.65	-2.86
		Axial	Vibration overload	-4.78	-2.86
First gear drive of the tail gearbox	Tail gearbox	Vertical	Vibration overload	-5.44	-2.86
		Axial	Vibration overload	-5.56	-2.86

There is a significant decrease in the values of the Dickey - Fuller criteria, which indicates a decrease in the degree of signal non-stationarity after the proposed partition. Also, there is a much smaller scope of the test values than in table 1, this makes it possible to assume that the degree of non-stationarity of the signals corresponds to the non-stationarity of the diagnosis process in this mode. All this makes it possible to better use the signals for the synthesis of predictive models.

5 Experiments and results

A four – layer recurrent neuron network with an input layer, two hidden layers with GRU-cell (Fig. 5) and an output layer with one linear neuron was chosen as a neu-ral network model. GRU [15] is a simplified model of a well – known LSTM cell with significantly fewer parame-ters. Through this, learning GRU is easier than LSTM, so it is gaining popularity in many real-world tasks.

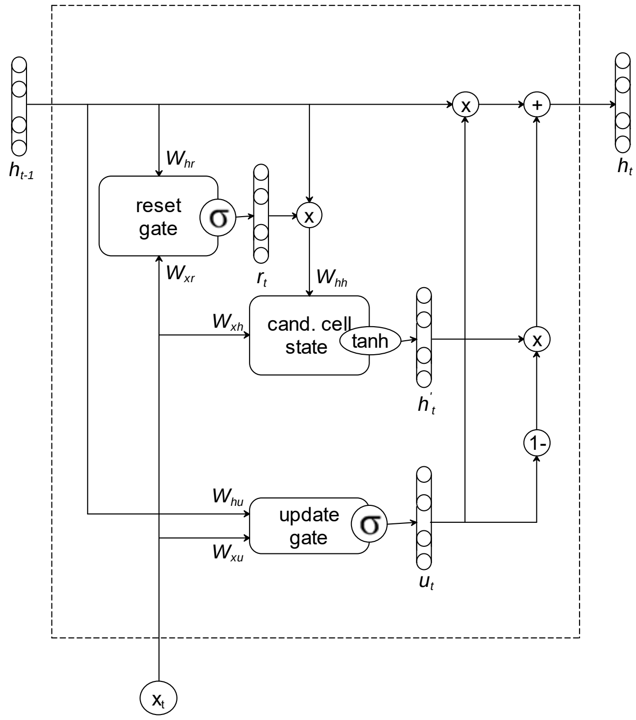

Fig. 5. The structure of the GRU-cell

At the input of the GRU-cell receives a vector *x*, which contains the current values of the signals. The output of the cell is calculated by the following formulas (3)-(6):

$$u_t = \sigma(W_{xu}x_t + W_{hu}h_{t-1} + b_u), \quad (6)$$

$$r_t = \sigma(W_{xr}x_t + W_{hr}h_{t-1} + b_r), \quad (7)$$

$$h'_t = \tanh(W_{xh'}x_t + W_{hh'}(r_t \otimes h_{t-1})), \quad (8)$$

$$h_t = (1-u_t) \otimes h'_t + u_t \otimes h_{t-1}. \quad (9)$$

The synthesized neural network model was tested and optimized on a sampling of signals during the diagnosis of the helicopter transmission at the second mode of the turbochargers of the engines. The total initial sample contained data collected in total for 1010 seconds for 22 diagnostic signals. She was divided into a training sample - 1 - 800 seconds, and the test - 801 - 1010 seconds.

As the input data of the models, the data for all signals for a given time window width were used. Data on one of the 22 signals with a given forecasting horizon, that is, a forward shift in the time scale of 120 seconds, were used alternately as initial data. The neural network error was calculated by formula 1. Neural network training was conducted over 250 epochs.

To improve the quality of the forecast, optimization of neural network hyperparameters was carried out. The results are given in tables 3 - 5.

Table 3. Results of the optimization of the batch size

Batch size	**Error on test sample**	**Standard deviation on the test sample**
5	0,0195	0,0121
10	0,0219	0,0127
20	0,0208	0,0156
40	**0,0178**	**0,0105**
80	0,0180	0,0123
100	0,0244	0,0291

Table 4. Results of optimal optimization algorithm selection

Name of the algorithm	**Error on test sample**	**Standard deviation on the test sample**
SGD	0,0207	0,0183
RMSprop	**0,0179**	**0,0103**
Adagrad	0,0184	0,0116
Adadelta	0,0182	0,0114
Adam	0,0211	0,0184
Adamax	0,0185	0,0122
Nadam	0,0193	0,0128

Table 5. Results of the optimization of the learning rate

Learning rate	**Error on test sample**	**Standard deviation on the test sample**
0,001	0,0187	0,0125
0,01	**0,0179**	**0,0089**
0,1	0,0216	0,0096
0,2	0,1030	0,2297
0,3	0,1176	0,1969

Fig. 6 shows a graph of the true and predicted in the neural network model values of the signal received on the intermediate gearbox (axial direction of measurement) and processed with parameter vibration ovetload that characterizes the state of the first gear drive of the intermediate gearbox during the second mode of turbochargers for the interval 801 - 1010 seconds (test sample).

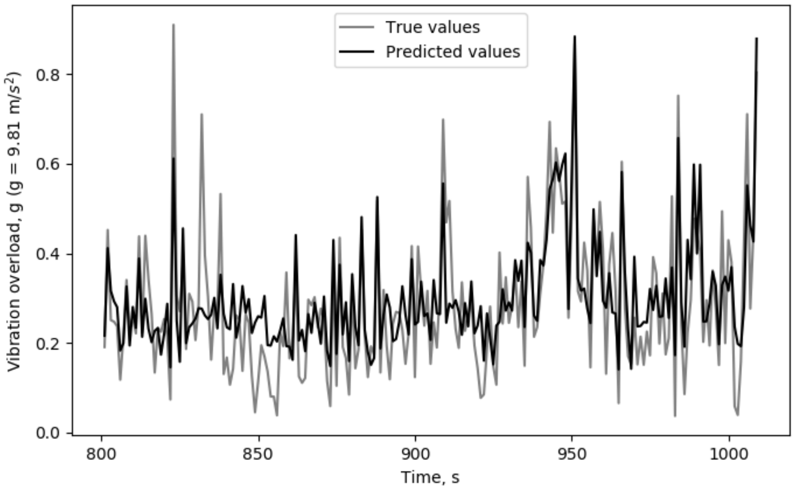

Fig. 6. True and predicted values of the signal

The prediction error is 0.0167 for the second mode of operation of turbochargers, which is 13.45 % in percentage terms. The forecast error for a signal without division into operating modes is 0.1096, which is 28.56% in percentage terms.

Therefore, if it is necessary to predict the state of the helicopter transmission for all modes, it is recommended to divide the signal by the proposed method, to predict each part of the signal using a predictive model and combine them on the basis of information about the duration of the operating modes.

6 Conclusion

In the conducted research of methods of analysis and transformation of non-stationary signals of diagnosing the method of reducing the degree of non-stationarity of the received signals based on expert information about the modes of operation during the diagnosis cycle was proposed.

The effectiveness of the method of reducing the degree of unsteadiness of signals based on expert information about the modes of operation during the diagnosis cycle is evidenced by a significant optimization of the value of the Dickey-fuller criterion after its application. This method, unlike most, does not require changing the internal structure of the signal, and works only by splitting the signal into several other signals, which can then be combined.

On the basis of processed signals, a neural network was synthesized to predict the state of the helicopter transmission and its hyperparameters were configured.

The results are planned to be used to improve the diagnostic quality of the helicopter transmission.

The method of transformation of nonstationary signals and the construction of neural network models developed and applied in the investigated method can be used to solve problems in which it is necessary to predict the future state of the object, by its diagnostic signals.

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