Method for Forecasting of Helicopters Aircraft Engines Technical State in Flight Modes Using Neural Networks

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Abstract

The work is devoted to the development of methods and algorithms for forecasting of helicopters turboshaft engines technical state in flight modes based on neural network technology. Methods of probability theory and mathematical statistics, methods of neuroinformatics, methods of the theory of information systems and data processing are applied in the work. The following results are obtained. The application of the neural network forecasting method proposed in the work, based on the approximation and extrapolation of the processes of changing the thermogasdynamic parameters of helicopters turboshaft engines on fixed time intervals (within the “sliding time window”), allows you to effectively solve the problems of forecasting its technical state. An analysis of the effectiveness of the neural network method for forecasting of helicopters turboshaft engines technical state under random interference shows its advantages over classical forecasting methods, which consist in providing higher forecasting accuracy for various forecast intervals (short-term, medium-term, long-term forecasting). The application of the developed neural network method makes it possible to detect the moments of discord in the time series, that is, the appearance of a trend in the parameters of helicopters turboshaft engines, which is a consequence of a qualitative change in engine characteristics, which allows prompt decisions to be made by the helicopter crew in flight mode.

Keywords

Turboshaft engines, recurrent neural network, GRNN-network, training error, gases temperature in front of the compressor turbine.

1. Introduction

Helicopters turboshaft engines (TE) as recoverable objects during their service life require continuous monitoring, the complexity of which depends on the level of automation of obtaining, processing, storing, documenting information processes about their current state, the sequence and methods of which determine the monitoring information technology. The main directions that determine the improvement of the quality of information technologies for monitoring of helicopters TE technical state should be considered the intellectualization of information processing processes using data mining methods that can improve the quality of recognition of gas turbine engines technical state under the action of the above uncertain factors, as well as the integration of information processes (distributed local databases and knowledge into a global database and knowledge).

Data mining methods are a new direction that complements and develops classical statistical research methods [1, 2]. Data Mining uses modern intelligent technologies, including neural networks,

COLINS-2022: 6th International Conference on Computational Linguistics and Intelligent Systems, May 12–13, 2022, Gliwice, Poland
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fuzzy logic, and expert systems. These technologies are used in this work to solve a wide range of tasks for monitoring of helicopter TE technical state.

An analysis of works in the field of monitoring of helicopters TE technical state based on neural networks [3, 4] shows that such work is currently underway, however, due to a number of reasons (secrecy, narrow specialization of the tasks being solved), most publications lack engineering methods, as well as theoretical and practical recommendations for solving such problems. In this paper, an engineering technique is developed for solving the problem of forecasting of helicopters TE technical state in flight modes using neural network technologies.

2. Literature review

Forecasting methods are divided into two groups [5]: intuitive and formalized. The first group of methods does not involve the development of forecasting models and reflects the judgments of experts. This group of methods is used when the object is too simple or so complex that it is impossible to analytically take into account the influence of external factors. The second group of methods is based on development a forecasting model. The most actively used in modeling complex processes are regression models. Regression prediction models are a function of the independent variable and parameters with an added random variable [6].

There are also models based on Markov chains, on classification-regression trees, on the basis of a genetic algorithm, on support vectors, on the basis of transfer functions, on fuzzy logic, etc. [7–9]. Also note that today there are many modifications of these models.

Due to the nonlinearity and variability of the characteristics of non-stationary time series of processes occurring in complex social, economic and socio-technical systems, traditional methods of analysis and modeling, for example, such as the integrated autoregression-moving average model (ARIMA, the Box-Jenkins model [10, 11]) and many others often lead to inaccurate or erroneous results.

The traditional approach to the analysis of non-stationary time series is based on using linear methods to reduce them to stationary time series, for example, the mentioned ARIMA models.

These models do not operate with distribution functions, but directly with elements of the time series. Series that do not fit into the framework of regression analysis are most often studied by various adaptive heuristic methods that do not have a clear mathematical justification. They assume that the series over a certain length can be described by a stationary model such as regression or autoregression, and the model parameters can be recalculated taking into account new information or taking into account the comparison of the predicted value with the fact. The disadvantage of these approaches is that the length of the region of possible stationarity is an unknown value, and at any time a trend change (disorder) can occur.

For non-stationary time series, indicators of one or another of its properties have their own specific form, which cannot be generalized to series of another type. For example, the linear trend indicator is not particularly effective for series with a quasi-periodic change, as is the indicator of the non-stationarity of the variance for series with a quasi-linear trend [12]. Moreover, indicators based on some average characteristics of the series (for example, the first few moments) do not form a basic system by which one can determine the trend of a random process change local in time.

In [13], nonparametric criteria for data estimation are given, using Monte Carlo mathematical modeling methods [14]. However, it should be noted that these methods are applicable only to stationary distributions and cannot be correctly used for the analysis of non-stationary time series.

For example, to model the trajectories of some random process with jumps, as applied to the prices of shares of enterprises in the aviation industry, stochastic differential equations with time-dependent drift and diffusion coefficients and the Erlang flow of events are used to describe jumps, but the practical implementation of random trajectories is based on the stationary Monte- Carlo for constant coefficients of the stochastic equation.

Considering all of the above, we can conclude that it is necessary to search for new methods for analyzing the dynamics of complex systems or new approaches to describing non-stationary time series, especially if self-organization of such systems is possible and there is a memory of previous states, for example, models and methods based on various types or combinations of machine learning algorithms such as neural networks, fuzzy logic, regression support vector machines, rule sets based on genetic programming of network applications, and a number of others.

3. Problem statement

Neural network forecasting refers to artificial intelligence methods that can solve multipurpose problems. The advantages of algorithms for neural network prediction of the technical state of complex dynamic objects using multilayer neural networks are based on good approximating abilities, and these neural networks can also be tuned using gradient methods, despite the huge number of weight coefficients. Neural networks with multiple layers are more powerful than those with a single layer only in the presence of non-linearity. These properties determine the prospects for using neural networks to predict the technical state of complex dynamic objects. The task of forecasting in the neural network basis is reduced to building a neural network model (predictor), which allows you to find the value of the vector Y at time $t + 1$ from the previous N values of the time series $Y\left(t-N+1\right),Y\left(t-N+2\right),...,Y\left(t\right)$, i.e. $Y\left(t+1\right)=f\left(Y\left(t\right),Y\left(t-1\right),...,Y\left(t-N+1\right)\right)$, where $Y(\bullet)$ – some non-linear vector function to be evaluated using a neural network; Y – vector of controlled parameters; t – discrete time. The accuracy of the forecast implemented using a neural network is estimated by the value $\left\|\varepsilon_{t+1}\right\|=\left\|Y_{t+1}-Y_{t+1}\right\|$, where Y_{t+1} – predicted value calculated by the neural network for time $t + 1$; Y_{t+1} – real value of vector Y at the same moment in time; ε_{t+1} – prediction error.

Currently, a number of forecasting methods are known, such as: heuristic methods, mathematical methods of temporal extrapolation, mathematical methods of spatial extrapolation, methods of modeling development processes, logical and structural methods [15, 16].

However, for their application, it is necessary to have large amounts of a priori information about the object under study, the value of the laws of distribution of their parameters, mathematical models that describe the processes of changing engine operating modes, within which it is possible to select criteria and predictive functions to solve the problem of predicting the technical state of complex dynamic objects. With individual forecasting, a priori information must be individual for each object. The disadvantages of the methods listed above include: low robustness under noise conditions; inability to issue a multi-parameter forecast taking into account the emergence of phenomena; the impossibility of prompt processing of information on a computer; the complexity of processing data presented in different types of scales, etc.

The solution of the problem of forecasting of helicopters TE technical state in a neural network basis is based on a priori information that is presented to the neural network in the form of ready-made solutions (task books), on the basis of which the process of its training (additional training) is carried out. This allows you to use such advantages of neural networks as: the ability to carry out a multi-parameter forecast; insensitivity to the lack of a priori and a posteriori information about the dynamics of forecasted processes; the possibility of processing data presented in different types of scales; the ability to generalize and retrain; robustness with respect to external disturbances. When evaluating the quality of the neural network, its input is data on the test sample, on the basis of which it calculates the vector of deviations (the difference between the output of the neural network and the desired characteristics).

There are two approaches to solving the problem of predicting of complex dynamic objects technical state, based on the use of:

– recurrent (dynamic) neural network that implements the dependence of the form $Y\left(t+1\right)=f\left(Y\left(t\right),Y\left(t-1\right),...,Y\left(t-N+1\right)\right)$;

– static neural network that implements time dependence $Y = f(t)$.

Methods for forecasting of aircraft turbojet engines technical state using neural networks are described in detail in the works of professor Sergey Zhernakov [17, 18], while the adaptation of these methods in relation to aircraft engines of helicopters is given in [19, 20]. However, this approach is based on the use of a static neural network that implements the time dependence $Y = f(t)$ and the construction of extrapolating functions $y(t)$ as a function of time $y_i(t) = f(t)$. Therefore, to forecast of helicopters TE technical state in flight modes, that is, in real time, this approach requires significant modification, in particular, the use of a recurrent (dynamic) neural network.

In this regard, this paper proposes a method based on the use of a recurrent (dynamic) neural network, the implementation of which is carried out as follows:

– time interval (monitoring interval) is set, which is a training sample for the neural network (t – neural network input; engine parameters y_1, y_2, …, y_n – neural network outputs);

– forecast step is set – $T_{forecast}$, taking into account the requirements for the forecast (short-term, medium-term, long-term forecast);

– after the neural network training process on the monitoring interval (T_{mon}), the forecasted values $y_i(t + T_{forecast})$ are calculated; for this, the time value $t + T_{forecast}$ is fed to neural network input;

– forecasting process is repeated in real time.

4. Mathematical description of the forecasting problem

When creating forecasts using neural networks, locally adjustable linear autoregressive forecasts are used, the coefficients of which are determined by the least squares method:

$$x_{t+1}^{f} = \alpha_0 x_t + \alpha_1 x_{t-1} + \ldots + \alpha_{m-1} x_{t-(m-1)} + \alpha_m. \tag{1}$$

Linear regression x_{t_r+1} for $x_{t_r}^{m} = \left(x_{t_r}, x_{t_r-1}, \ldots, x_{t_r-(m-1)}\right)$, $r = 1\ldots k$, established by the least squares method, α_t – values of α_t, that minimize the sum $\sum_{r=1}^{k}\left(x_{t_r+1} - \alpha_0 x_{t_r} - \alpha_1 x_{t_r-1} - \alpha_{m-1} x_{t_r-(m-1)} - \alpha_m\right)^2$. To set SNN to latest m-chronology $\left(x_t^m, y_t^m\right)$, one can look at the nearest point k that maximize the function $\rho\left(x_n^m, x_t^m\right) + \rho\left(y_n^m, y_t^m\right)$, $i = m$, $m + 1$, t. Thus, we have obtained a set of k simultaneous m-chronologies in both series:

$$\begin{matrix} x_{i_1}^{m} & y_{t_1}^{m} \\ x_{i_2}^{m} & y_{t_2}^{m} \\ \ldots & \ldots \\ x_{i_k}^{m} & y_{t_k}^{m} \end{matrix} \tag{2}$$

Predictions for x_{t+1} and y_{t+1} can be obtained from a linear autoregression predictor with different coefficients from least squares method:

$$x_{t+1}^{f} = \alpha_0 x_t + \alpha_1 x_{t-1} + \ldots + \alpha_{m-1} x_{t-(m-1)} + \alpha_m; \tag{3}$$

$$y_{t+1}^{f} = \beta_0 y_t + \beta_1 y_{t-1} + \ldots + \beta_{m-1} y_{t-(m-1)} + \beta_m. \tag{4}$$

Coefficient α_t and β_t are the values of α_t and β_t respectively and minimize the sums:

$$\sum_{r=1}^{k}\left(x_{t_r+1} - \alpha_0 x_{t_r} - \alpha_1 x_{t_r-1} - \alpha_{m-1} x_{t_r-(m-1)} - \alpha_m\right)^2; \tag{5}$$

$$\sum_{r=1}^{k}\left(y_{t_r+1} - \beta_0 y_{t_r} - \beta_1 y_{t_r-1} - \beta_{m-1} y_{t_r-(m-1)} - \beta_m\right)^2. \tag{6}$$

5. Selection of neural network architecture, structure and training algorithm

When selecting a network architecture, it is common to try several configurations with different numbers of elements. Based on the fact that the prediction problem is a special case of the regression problem, it follows that it can be solved by the following types of neural networks: multilayer perceptron (MLP), radial basis network (RBF), generalized regression network (GRNN), Volterri network and Elman network.

When solving the problem of forecasting of helicopters TE technical state in flight modes (in real time), a generalized regression network was chosen as a neural network that implements methods of nuclear approximation. In regression problems, neural network output can be considered as the expected value of the model at a given point in the space of inputs. This expected value is related to the probability density of the joint distribution of the input and output data. A Gaussian kernel function is placed at the location of each training observation. It is believed that each observation indicates some confidence that the response surface at a given point has a certain height, and this confidence decreases as we move away from the point. The GRNN-network copies all training observations into itself and uses them to evaluate the response at an arbitrary point. The final output estimate of the network is obtained as a weighted average of the outputs over all training observations, where the weight values reflect the distance from these observations to the point at which the estimate is made (and thus closer points contribute more to the estimate). The advantage of the GRNN-network can be considered the certainty of the structure: the network actually contains all the training data [21]. The structure of the GRNN neural network is shown in fig. 1.

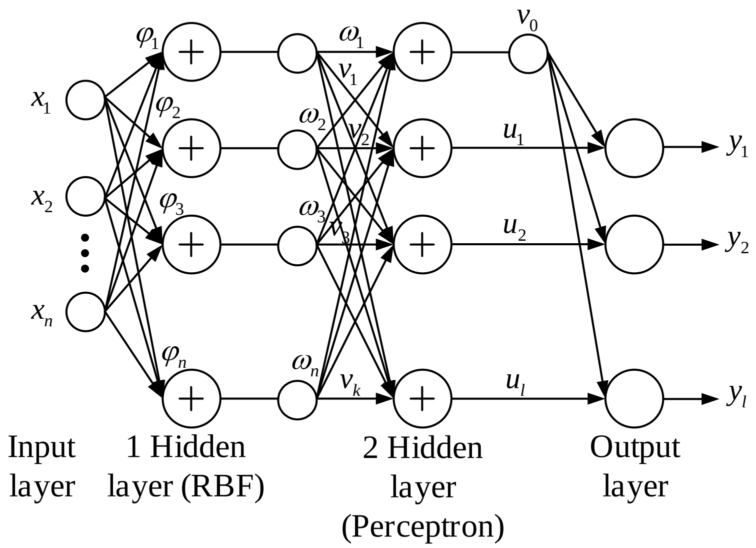


Figure 1: Generalized structure of the GRNN-network

GRNN-network has two hidden layers: layer of radial elements and layer of elements that form a weighted sum for the corresponding element of the output layer. The output layer determines the weighted average by dividing the weighted sum by the sum of the weights. The Gaussian function is used as the radial function.

The input layer transmits signals to the first intermediate layer of neurons, which are radially symmetrical. They carry information about these training cases or their clusters and transfer it to the second intermediate layer. It forms weighted sums for all elements of the output layer and the sum of weights calculated by a special element. If we designate the output of the *i*-th neuron of the RBF layer as v_i, then the output signal of the *l*-th neuron of the second intermediate layer is calculated according to the expression:

$$u_l = \sum_{i=1}^{k} v_i; \tag{7}$$

where k – number of neurons in the RBF layer.

Taking the weight coefficient of the *i*-th neuron of the RBF layer as ω_i, we obtain an expression for the sum of the weights:

$$v_0 = \sum_{i=1}^{k} \omega_i. \tag{8}$$

The output layer divides the weighted sums by the sum of the weights and produces the final forecast. Taking it for y_l, we get:

$$y_l = \frac{u_l}{v_0}. \tag{9}$$

Let us consider the principles of functioning of the first intermediate layer, the structure of which is shown in fig. 2.

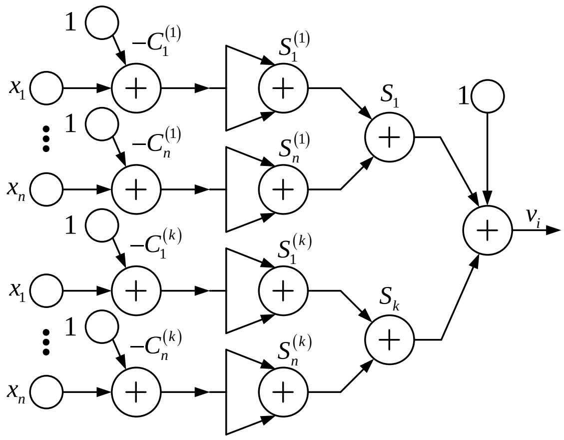


Figure 2: RBF layer structure of GRNN-network

The vector *x* is fed to the input of the radial elements from the input layer. The basis functions of the RBF layer are given by the matrix *Q*, but in practical terms it is more convenient to use the correlation matrix *C* to describe the elements, which is obtained from the matrix *Q* as follows.

$$C = Q^T Q. \tag{10}$$

The center of the *i*-th neuron of the radial layer will be taken as c_i. The final result of processing input signals S_j is calculated according to the expressions:

$$S_j^{(t)} = -\frac{1}{2}\sum_{t=1}^{n}\left(x_t - c_i^{(t)}\right)^2; \tag{11}$$

$$S_t = \sum_{j=1}^{n} S_j^{(t)}; \tag{12}$$

$$v_i = \sum_{t=1}^{k} e^{-\frac{S_t \omega_t}{2\sigma_t^2}}. \tag{13}$$

Then the vector of output signals *v* is transferred to the input of the second intermediate layer of the network. Neural network training must be performed separately for each time series, since an attempt to predict a series on which the network has not been trained will lead to an erroneous result [22]. As a training algorithm, a modified backpropagation algorithm with automatic correction of the training step length (ParTan) [23] was used.

6. Input data description

The following helicopters TE thermogasdynamic parameters, recorded on helicopter board, are used as input data in this work, reduced to absolute parameters, according to the theory of gas-dynamic similarity developed by Professor Valery Avgustinovich [24]: n_{TC} – gas-generator rotor r.p.m., T_G – gases temperature in front of the compressor turbine (table 1).

Table 1
Fragment of the training sample during the operation of helicopter aircraft TE (on the example of TV3-117 aircraft TE)

Time	n_{TC}	T_G
88	0.944	0.616
89.04	0.908	0.613
89.48	0.943	0.612
90.27	0.949	0.611
90.71	0.922	0.610
91.68	0.893	0.609
92.03	0.921	0.608

92.69	0.982	0.608
93.57	0.985	0.609
94.12	0.986	0.607
94.36	0.985	0.605

7. Results and discussion

The article studies the dependence of the quality of forecasting on the parameters of the training algorithm and the structure of the neural network: the number of neurons in the 1st hidden layer is 8, the number of neurons in the 2nd hidden layer is 6, the forecast range is 5, the training algorithm is ParTan, the algorithm parameters are optimal, the partition of readings of a series into sets is optimal. In fig. 3 shows a graph of the neural network training error.

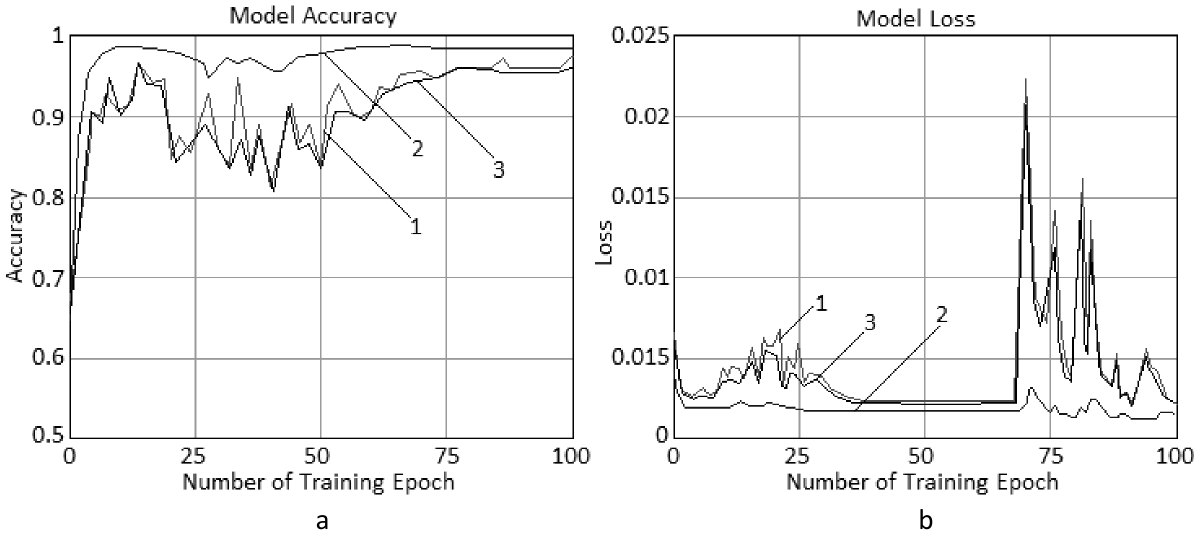


Figure 3: Neural network training error graph: *a – Accuracy* indicator; *b – Loss* indicator (1 – train, 2 – test, 3 – control)

The research results showed that the quality of forecasting depends, first of all, on dividing the samples of the series into three sets – training, testing and control. The best forecast quality is achieved with a sample size ratio of 60:20:20. It is obvious that the accuracy of the forecast will fall as the range increases. The optimal values of the algorithm parameters are: the training rate coefficient η = 0.7, the training moment coefficient μ = 0.9, the number of iterations before memorization N = 20, the change in the training rate coefficient α = 0.1. The number of neurons in the hidden layers of the neural network is determined individually for each time series.

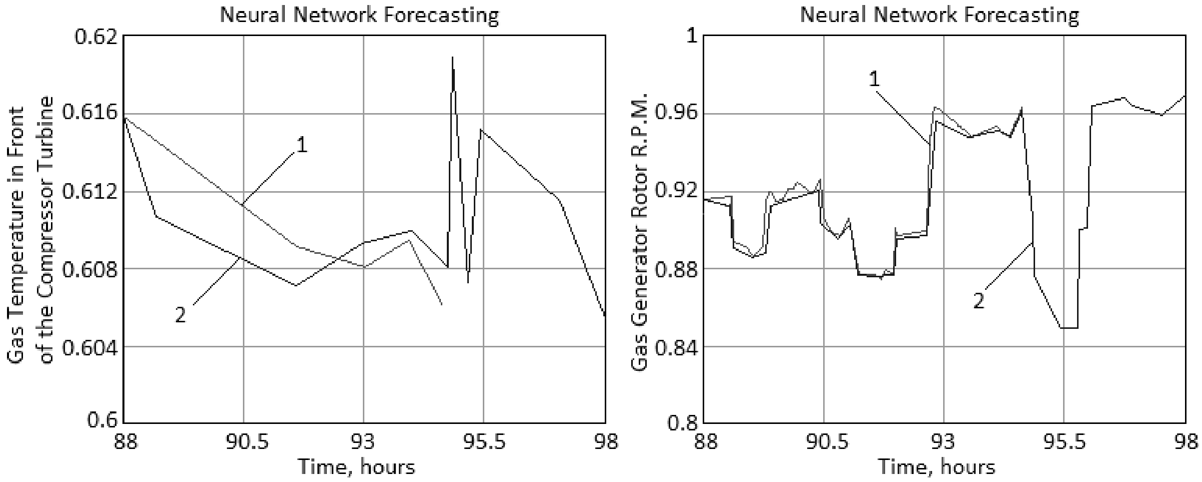
In table 2 and 3 shows the result of GRNN-network training statistics for parameter n_{TC} – gas-generator rotor r.p.m. and T_G – gases temperature in front of the compressor.

Table 2
GRNN-network training statistics for parameter n_{TC} – gas-generator rotor r.p.m.

Final statistics	Algorithm parameters		
	η = 0.25 μ = 0.5	η = 0.5 μ = 0.9	η = 0.7 μ = 0.9
Error mathematical expectation	0.1226	0.0519	0.0113
Error variance	0.0021	0.0011	0.0008
Error standard deviation	0.0458	0.0331	0.0283

Table 3
GRNN-network training statistics for parameter T_G – gases temperature in front of the compressor turbine

Final statistics	Algorithm parameters		
	η = 0.25 μ = 0.5	η = 0.5 μ = 0.9	η = 0.7 μ = 0.9
Error mathematical expectation	0.1534	0.0582	0.0129
Error variance	0.0026	0.0014	0.0013
Error standard deviation	0.0510	0.0374	0.0361



a
b

Figure 4: Results of forecasting the thermogasdynamic parameters of TV3-117 aircraft engine (1 – real value; 2 – forecasting using a neural network), t = 94.65 hours – forecast moment: a – T_G (gases temperature in front of the compressor turbine); b – n_{TC} (gas-generator rotor r.p.m.)

When evaluating the effectiveness of the developed neural network forecasting of helicopters TE technical state, similarly to [9, 10], a comparative analysis is carried out with a number of classical methods: exponential smoothing (MES), moving average (MAM), least squares method (MLS). Forecasting according to the moving average method is carried out according to the expression:

$$y_{t+1} = \frac{1}{N}\sum_{b=0}^{N} y_{t-b+1}; \tag{14}$$

where N – number of previous periods included in the moving average; y_t – actual value at the moment of time; y_{t+1} – forecasted value at time t + 1.

Forecasting according to the exponential smoothing method is carried out according to the expression:

$$y_{t+1} = y_t + \alpha(A_t - y_t) + \alpha A_t + (1 - \alpha)y_t; \tag{15}$$

where y_{t+1} – forecasted value of the parameter based on the previous value of y_t adjusted for the forecasting error $A_t - y_t$ and a weighting factor α ($0 < \alpha < 1$).

On fig. 5 shows the results of a comparative analysis of the neural network and classical methods for forecasting of helicopters TE technical state (for example, the TV3-117 engine) for gases temperature in front of the compressor turbine, as the most significant parameter, where it is indicated: 1 – real value of gases temperature in front of the compressor turbine; 2 – value of gases temperature in front of the compressor turbine, calculated using a neural network; 3 – value of gases temperature in front of the compressor turbine, calculated on the basis of the moving average method; 4 – value gases temperature in front of the compressor turbine, calculated using the exponential smoothing method; 5 – value of gases temperature in front of the compressor turbine, calculated using the least squares method.

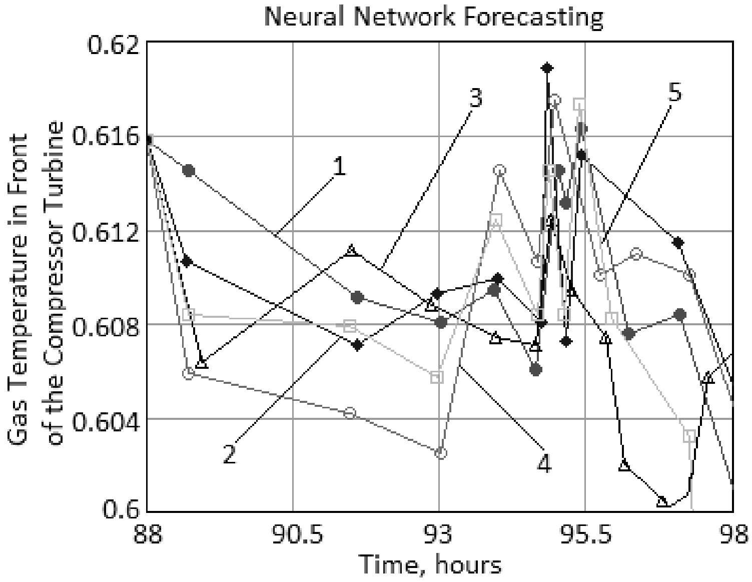


Figure 5: Results of forecasting the gases temperature in front of the compressor turbine

In the process of solving the forecasting problem, the step Δ*t* corresponded to: in the short-term forecasting problem, Δ*t* = 0.4 hours; in the problem of medium-term forecasting Δ*t* = 1.75 hours; in the problem of long-term forecasting Δ*t* = 3.35 hours.

On fig. 5 it is assumed that the forecast moment is *t* = 94.65 hours; time interval *t* ϵ [94.65; 95.05] corresponds to short-term forecasting; *t* ϵ [94.65; 96.40] – medium-term forecasting; *t* ϵ [94.65; 98.0] – long-term forecasting.

The results of a comparative analysis of the work of classical and neural network methods for forecasting of helicopters TE technical state are given in table 4 and in fig. 6, where the solid line corresponds to forecast errors in the absence of noise, and the dash-dotted line corresponds to forecast errors in the presence of additive interference (noise).

Table 4

Results of comparative analysis of the work of classical and neural network methods for forecasting of helicopters aircraft TE technical state

Forecasting method	Method name	Engine parameter forecasting error					
		n_{TC}, %			T_G, %		
		S	M	L	S	M	L
Classic (no noise)	MAM	0.528	0.661	1.317	0.365	1.155	1.556
	MES	0.297	0.457	1.259	0.583	1.264	1.653
	MLS	0.692	0.795	1.693	0.936	1.446	2.552
Neural network (no noise)	NN	0.235	0.304	0.465	0.219	0.304	0.425
Classic (with noise)	MAM	1.524	1.863	2.408	1.227	1.373	1.969
	MES	1.726	1.742	2.335	1.495	1.701	2.273
	MLS	2.148	2.204	2.447	1.883	2.431	3.378
Neural network (with noise)	NN	0.682	0.719	0.726	0.413	0.583	0.620

In table 4 the following designations are used: S – short-term forecast; M – medium-term forecast; L – long-term forecast; MAM – moving average method; MES – exponential smoothing method; MLS – least squares method. In table 4 shows the forecast results for two cases:

– "clean" measurements obtained in the absence of additional random noise;

– measurements in the presence of additive random interference in the form of white noise (σ = 0.01; M = 0).

In fig. 6 gases temperature in front of the compressor turbine forecast error $\delta_{i\,forecast} = \max_i \left|\delta_{i\,forecast}\right|$ corresponds to the use of: 1, 2 – moving average method; 3, 4 – exponential smoothing method; 5, 6 – least squares method; 7, 8 – neural network method. In this case, the solid line corresponds to forecast errors in the absence of noise, and the dash-dotted line corresponds to forecast errors in the presence of an additive obstacle (noise).

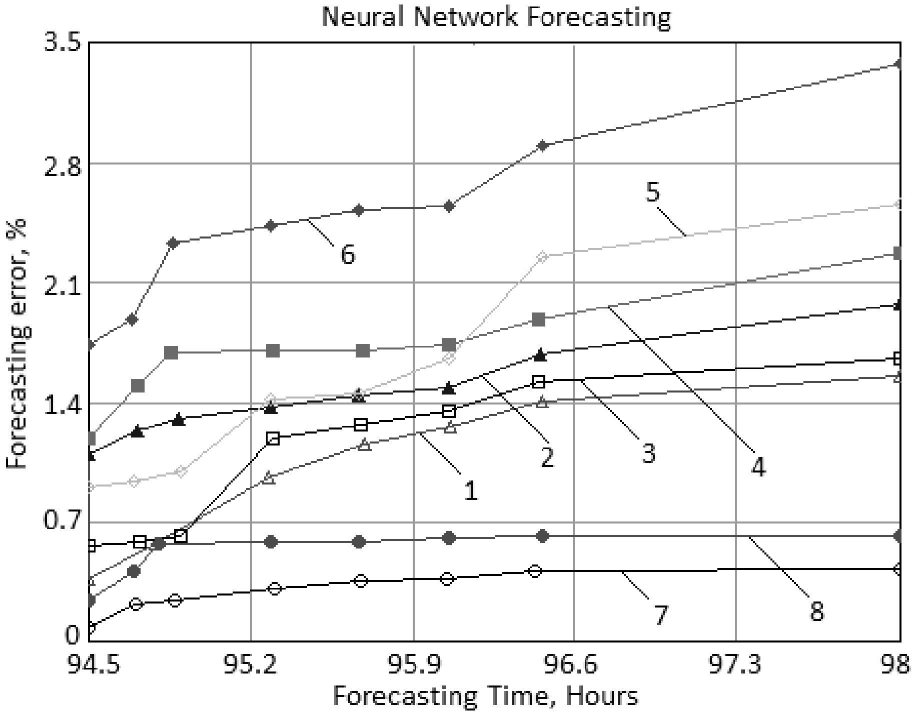


Figure 6: Dependence of forecast error change on the forecast interval

Analysis of the results given in table 4 and in fig. 6 indicates a high quality of forecasting using the neural network method. Thus, in the absence of additive interference, the accuracy of short-term, medium-term and long-term gases temperature forecasts using neural networks is higher compared to the least squares method, respectively, by 4.27; 4.78 and 6.0 times. A similar forecasting error based on the moving average method for short-term, medium-term and long-term gases temperature forecasts is higher compared to the neural network method, respectively, by 1.67; 3.80 and 3.66 times; and for the exponential smoothing method in similar areas of gases temperature forecasting, the forecasting error is also higher compared to the neural network method, respectively, by 2.66; 4.16 and 3.89 times. In the presence of interference, the accuracy of short-term, medium-term and long-term gases temperature forecasts using the neural network method is also higher in comparison with the least squares method, respectively, by 4.56; 4.17 and 5.45 times. The error of the moving average method under these conditions at similar intervals for forecasting the gases temperature is significantly higher compared to the neural network method, respectively, by 2.97; 2.36 and 3.18 times; and for the exponential smoothing method under these conditions, the error is also higher compared to the neural network method, respectively, by 3.62; 2.92 and 3.67 times.

The solution of the above task of forecasting gases temperature in front of the compressor turbine of TV3-117 aircraft engine based on neural networks showed that in the period from 94.65 to 98.0 hours there is a steady tendency to degradation of this parameter, which indicates a malfunction in the operation of the aircraft engine. The forecasting results show that starting from t = 95 hours, the helicopter must immediately land on the ground due to the risk of engine failure. A timely decision will prevent serious damage to the engine compressor assembly, which in this case is the result of the surge of the first stage compressor blades.

The developed neural network forecasting method can be effectively used to predict a wide class of characteristics of helicopters aircraft engines, and, in particular, to predict such an important parameter as the remaining engine life.

8. Conclusions

The application of the developed neural network forecasting method based on approximation and extrapolation of the processes of changing engine thermogasdynamic parameters at fixed intervals of the time window (within the "sliding time window") allows you to effectively solve the problems of forecasting of helicopter aircraft engines technical state in flight modes.

On the example of real data of TV3-117aircraft engine, registered on board the Mi-8MTV helicopter in flight mode, it is shown that the accuracy of the short-term (forecasting interval – 94.65...95.05 hours; forecasting step Δt = 0.4 hours), medium-term (forecasting interval – 94.65...96.40 hours; forecasting step Δt = 1.75 hours), long-term forecasting (forecasting interval – 94.65...98.0 hours; forecasting step Δt = 3.35 hours) is significantly higher compared to least squares method. Other classical forecasting methods (moving average and exponential smoothing) also lose in accuracy in relation to the neural network method both in the absence and in the presence of interference.

Analysis of the effectiveness of the neural network method for forecasting of helicopter aircraft engines technical state in flight modes under the influence of random interference shows its advantages over classical forecasting methods, which consists in providing higher forecasting accuracy for various forecast intervals (short-term, medium-term, long-term forecasting).

The application of the developed neural network method makes it possible to detect the moments of discord in the time series, i.e., the appearance of a trend in the parameters of aircraft engines of helicopters, which is a consequence of a qualitative change in the characteristics of the engine, which makes it possible to make timely decisions to change the operating mode of the engine.

9. References

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