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## Perspective development of diagnostic systems of aircraft structures and units

To cite this article: S V Gushchin and A P Polonsky 2019 *IOP Conf. Ser.: Mater. Sci. Eng.* **632** 012094

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# Perspective development of diagnostic systems of aircraft structures and units

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**Abstract.** The article deals with information-diagnostic systems of detection of defects and malfunctions as applied to aircraft structures and units. **Methods.** Analysis of modern methods of nondestructive testing is carried out. It is suggested to use the combined diagnostics of aircraft structures and systems with the use of vibrometry in combination with the determination of the appearance of metal particles in the oil, their quantity and size. The possibility of using acoustic emission is considered. **Results.** The article compares the accuracy and reliability of the inspection of aircraft parts, assemblies and systems by different methods. **Conclusion.** We have drawn conclusions about the prospects of the proposed method of diagnostics. It is shown that trained neural networks are able to provide information about the presence of defects, their size and location when working in the software of information-diagnostic systems.

## 1. Introduction

The serial production of the MS-21 aircraft at the Irkutsk Aviation Plant, which uses modern materials, including light alloys and polymeric composite materials, raises the question of methods and means of diagnosing the aircraft parts, components and systems during production and during its operation.

Specialized information-diagnostic systems (SIS) are widely used in the aviation industry and airlines of foreign countries).

In general terms, the concept of SIS corresponds to the definition of a classical system of technical diagnostics, which is known to be a set of:

- the diagnosis object, in this case specific aircraft systems and units;
- diagnostic hardware, i.e. specific electromechanical and electronic equipment (Hardware);
- procedures (algorithms and programs) for diagnosis, processing and analysis of relevant results, i.e. software (Software).

In general, the SIS interacts with the on-board recorder, and the parameters recorded by the sensors of the on-board recorder and additional sensors of the IRS itself are transferred through analogue-digital converters to the on-board computer processor, which performs accumulation and primary processing of the registered information and then to the recorder's storage and to the corresponding devices and indicators in the cockpit, which in general forms the on-board measuring and computing complex.

## 2. Results

After landing the aircraft, the information of the on-board computer, usually pre-compressed, is copied to a removable storage medium and entered into the memory of a powerful ground computer, with the help of which the following basic operations are performed on the ground computer system:



- reproduction and secondary processing of flight information, mainly filtering of various discharges and emissions;
- functional and statistical analysis of this processed information;
- algorithmized procedures for diagnostics and forecasting of aircraft technical condition, its main systems, units and equipment;

The objectives of the SIS are:

- Increase of operational reliability and safety of aircraft flights due to timely detection of bad condition of vital dynamically loaded units;
- creation of more reliable designs on the basis of in-depth reliable analysis of physical and statistical patterns of occurrence and development of various failures;
- provision of the full development of the resource potential of aircraft design and operation.

The principal requirements for SIS are as follows:

- open source software architecture;
- modular structure of on-board and onshore complexes based on the most advanced relevant technological achievements;

In addition, the software implementation of the SIS must meet the following requirements:

- use of modern algorithms of technical diagnostics and forecasting;
- user-friendly interface with a middle-skilled operator;
- protection of information from unauthorized use.

The main method of monitoring and diagnosing the technical condition of vital LA units used in all modifications of the SIS is vibration diagnostics based on the following approved positions.

1. Even with the perfect balance and serviceability of all its rotating units, the aircraft is characterized by so-called normal-induced vibrations, which are characterized by the following laws:

- the level of vibration increases significantly when the natural frequencies of the fuselage elastic oscillation are close to the frequency of any passing harmonica in the vertical or horizontal plane;

2. In addition to these normally occurring vibrations of any aircraft or vehicle, there are also so-called technological or operational vibrations, the sources of which are:

- static and dynamic unbalance of shafts, spinning gears and bearing housings;
- unsteady frictional forces in gearing and bearings;
- manufacturing defects in the manufacture of various parts;
- heterogeneous operational wear of the working surfaces of the screw blades, fan blades and turbochargers of engines, gear teeth, tracks and bearing bodies;
- fatigue damage or destruction of parts during operation.

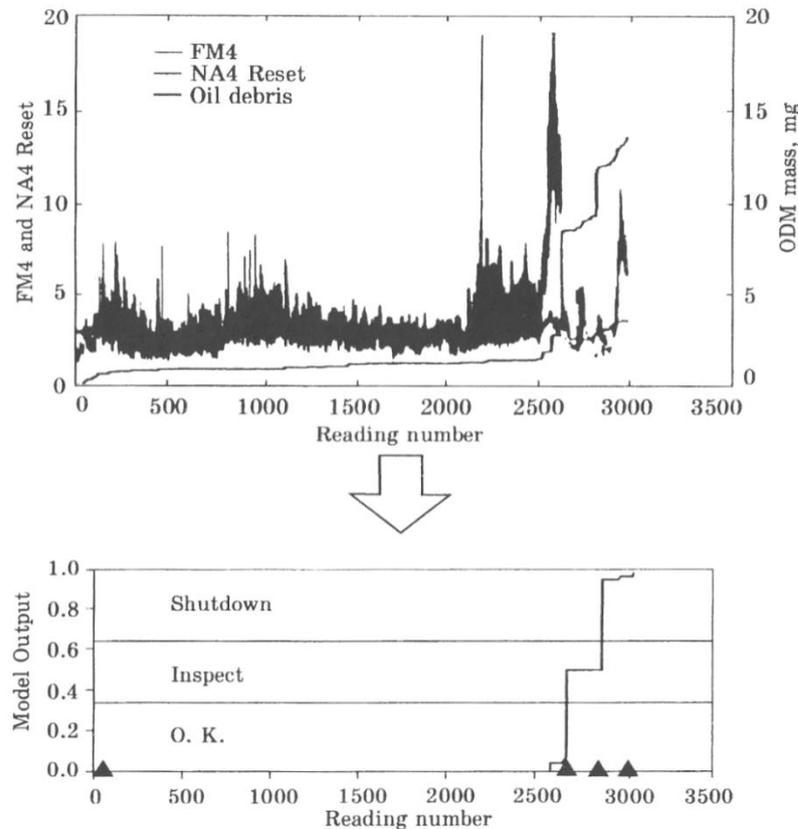
3. Technological (operational) vibrations are characterized by the presence of all harmonics in the linear spectrum, not only "passing" harmonics, with the highest amplitude and, accordingly, diagnostic value of the first screw harmonica.

4. The basic vibration parameter to be diagnosed is vibration acceleration, measured by accelerometers of different designs.

5. Fault detection consists in comparing the coded difference spectrum of the controlled unit and the recognition matrix, and the efficiency of the detection of various faults can be significantly increased by the definition and comparison of state vectors on several typical modes of operation of the unit.

6. Ultimately, the detection of defective states of the monitored unit is based on:

- Analysis of patterns of characteristic changes in vibration parameters such as trend, jump, ejection and spread, compared with the corresponding reference characteristics of a working unit;
- application of mathematical predictive models (exponential, Bayesian, etc.);
- use of additional objective information (BUR, chip detector in the oil of the unit, optical sensors, acoustic emission, etc.).



**Figure 1.** Diagnosis of machine malfunctions by vibration level and metal shavings in the oil

7. The efficiency of vibration diagnostics is largely determined by the nature of vibration signal propagation, depending on the elastic mass and dissipative properties of multi-coupled systems such as aircraft units.

Experimental studies aimed at improving the reliability and accuracy of the SIS functioning provide for the monitoring of the units' performance based on two diagnostic parameters.

The first and the main diagnostic parameter is still the vibrating one, and the second one is the metallic particles (chips) in the oil of the unit or the acoustic emission (noise spectrum) during its operation.

Alarm chips and magnetic plugs in engine and gearbox oil systems have been used for a long time on the overwhelming majority of foreign and domestic aircraft, and now there is a much more advanced system of technical diagnostics. Sensors of this system detect not only the event of occurrence of metal particles in the oil, but also the quantity and size of these particles, on the basis of which the total mass of the separated metal is calculated in real time in the on-board computer. These data correlate with the corresponding vibration diagnostic data and as a result, algorithmized information on the level of serviceability (damage) of the internal cavity of the control unit is provided to the cockpit (after the landing of the aircraft - and to the ground station). The algorithm of signal correlation between two independent technical diagnostics tools provides both reliability and accuracy of the resulting assessment with proper serviceability and accuracy of the diagnostics tools themselves. (see Fig. 1).

The abscissa axis at the top and bottom of the figure shows the race time of the defective machine on the stand (Readingnumber) in minutes:

- on the ordinate axis in the upper left part of the figure - generalized statistical vibration parameters (FM4 and NA4 Reset), which are the physical meaning of the integral parameters of the excess;
- along the ordinate axis in the upper right part of the figure - total mass of metal chips (Oildebris) in mgg (ODMmass, mg);

- on the ordinate axis in the lower part of the figure - generalized normalized indicator of the unit's technical condition (ModelOutput);
- three regulated levels of technical condition and corresponding recommended actions by ground personnel mean normal condition (A.C.), the need for thorough inspection (Inspect) and suspension from operation (Shutdown).

As can be seen, the monitoring results of the two independent channels are in good agreement with each other, which will allow excluding false positives of the SIS [1].

The level and spectrum of acoustic noise generated by operating mechanisms is a consequence of the interaction of their parts, including in conditions of instability, roughness and damage to contact surfaces, etc.

As a diagnostic parameter it is expedient to use the spectrum of noise and to estimate their technical condition by changing the levels of frequency bands, typical for control units or parts of the unit. In general, acoustic emission is one of the most sensitive and accurate known methods of detecting deformations and fractures of metal parts.

The main problems of creating acoustic monitoring as an additional to the vibrational (ie, in general, vibroacoustic monitoring) is the low ratio of the useful signal in measurements of spectrograms to interference, especially in the low-frequency range of the spectrum, as well as the installation and provision of trouble-free operation of microphones. It is shown, for example, that when a standard miniature microphone is placed at a distance of about 1 m from the control gearbox, it is possible to diagnose the contact zone of gears with the area of no more than 4 cm only at the frequency of acoustic signals not less than 1.5 kgts, and therefore further studies in the direction under consideration are planned to focus on the high-frequency part of the acoustic spectrum [2].

The SIS software can be based on neural networks. Neural networks based on a nervous system biology model represent an exceptionally powerful method of mathematical modeling.

Neural networks are trained using examples when a neural network user selects a representative sample and then launches a learning algorithm that automatically perceives the data structure. At the same time, the neural network can be trained in such a way as to distinguish the condition of the given technical system (unit, node) from the faulty condition and to warn about the occurrence of a pre-fault condition in due time. Finally, with the help of a neural network that receives signals from the sensors installed on this unit, it is possible to control the various parameters of the unit in a targeted (rational, optimal) way [4].

Neural networks trained on the basis of experimental data are of the greatest value, therefore, as the results of special tests are obtained and the experience of mass operation is accumulated, both training and testing of neural networks are carried out mainly using the database of relevant experimental data [3].

The following functions are available for creating a neural network in the NeuralNetworksToolbox package of MATLAB [5]:

`net= newff (PR, [S1 S2...SNI], {TF1 TF2...TFNI}, BTF, BLF, PF)` – the function of creating multilayer NS with training by the method of reverse error distribution.:

PR –  $R \times 2$  – matrix of minimum and maximum values of R input elements;

Si – the size of the i-th hidden layer for NI layers;

TFi – i-layer neurons activation function, default 'tansig';

BTF – network learning function, default 'traingd';

BLF – default scales and offsets, default 'learnf';

PF – error function, default 'mse'.

`net=newrbe(P,T,goal,spread)` – network creation function with radial basic elements with zero error on the training sample:

P –  $R \times Q$  – matrix Q of input vectors;

T –  $S \times Q$  – matrix Q of target vectors;

spread – deviation (default 1,0).

neural network training functions

`net=train(net,P,T)` – neural network learning function:

`net` – untrained network name;

`P` – matrix of input neural network values;

`T` – matrix of output neural network values.

The teach-in method is defined using the `net.trainFcn` parameter, e.g. `net.trainFcn = 'trainbfg'`.

Functions of using neural networks

`[Y]=sim(net,P)` – function that simulates neural network operation:

`net` – network name;

`P` – network inputs.

For processing of experimental data, research of the gas turbine engine (Fig. 2), obtained during the check of the technical condition of engines NK-8-2U was the use of SIS software package Simulink/Matlab.

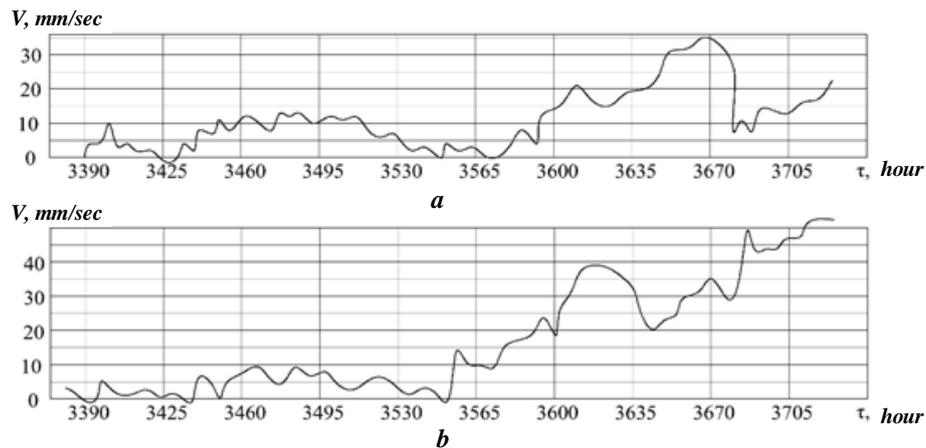
Experimental data [7] have allowed to receive an input vector of sizes of operating time of the engine in hours and vibrosopes on forward and back support of the engine.

Approximation of the function with the help of the neural network was carried out on a segment at the operating time [3390 3635], using the following experimental data:

`P= [3390,3425,3460,3495,3530,3565,3600,3635]` – hours worked;

`T1= [0,0,10,10,6,4,14,20]` – vibration speed in mm/s at the front engine mount;

`T2= [0,2,8,8,6,10,20,30]` – vibration speed in mm/s at the rear of the engine.



**Figure 2.** Deviation of the recorded vibration velocity in the front (a) and rear (b) mounts of the turbojet engine depending on the operating time

To estimate the number of neurons in hidden layers of homogeneous neural networks, a formula can be used to estimate the required number of synaptic weights  $L_w$  (in a multilayer network with sigmoid transfer functions)

$$(mN)/(1+\log_2 N) \leq L_w \leq m(N/m+1)(n+m+1)+m,$$

where  $n$  – input dimension;  $m$  – output dimension;  $N$  – number of elements of the training sample.

In our case, the input signal dimension  $n = 1$ , the output signal dimension  $m = 1$ , the number of training sample elements  $N = 8$ , then the required number of synaptic weights:

$$(1 \times 8)/(1 + \log_2 8) \leq L_w \leq 1(8/1 + 1)(1 + 1 + 1) + 1$$

$$3,66 \leq L_w \leq 28.$$

You can see that the number of synaptic scales can be small, and the hidden layer - only one. Create a direct distribution network with four neurons in the hidden layer and one (set by default) in the output layer:

$$\text{net1} = \text{newff}(P, T1, 4).$$

The next step is to train the network:

$$\text{net1} = \text{train}(\text{net1}, P, T1).$$

The train function teaches the specified net network using the input vector P and output vector T1. The result (structure of the trained network) is assigned to the variable net1.

The learning curve is checked using the neural network function:

$$Y1 = \text{sim}(\text{net1}, P).$$

The result is the vector of outputs Y1 as a result of the influence of input vectors on the trained network:

$$Y1 = [2.0105, 0.4258, 6.2591, 10.0477, 12.9218, 14.2367, 14.7273, 19.9605].$$

If you compare the result with the required:

$$T1 = [0, 0, 10, 10, 6, 4, 14, 20],$$

we can see that the accuracy of the approximation is not high enough.

By increasing the number of hidden neurons, up to six better results can be achieved:

$$Y1 = [0.0180, 0.0059, 9.9088, 10.1282, 5.9983, 1.2487, 13.9986, 19.9941].$$

In the course of testing of the SIS by experimental data of the vibration velocity on the rear motor support, it was obtained that the data of real measurements of T2, and obtained in the course of SIS operation with 6 hidden neurons Y2, are quite well coordinated.

$$T2 = [0, 2, 8, 8, 6, 10, 20, 30]$$

$$Y2 = [-2.2752, 2.2506, 7.9519, 6.6849, 6.7998, 9.9014, 19.1032, 24.5177]$$

Compare the direct distribution network with the radial base element network:

$$\text{net1rbe} = \text{newrbe}(P, T1)$$

This type of network takes less time to learn. Checking the results of the network operation using the sim function taking into account the input operating time vector P:

$$Y1R = \text{sim}(\text{net1rbe}, P),$$

Comparison of vibration velocity vectors on the engine front support shows their practical coincidence:

$$T1 = [0, 0, 10, 10, 6, 4, 14, 20],$$

$$Y1R = [-0.0000, -0.0000, 10.0000, 10.0000, 6.0000, 4.0000, 14.0000, 20.0000].$$

The use of a network with radial basic elements gives similar results for the rear engine support:

$$T2 = [0, 2, 8, 8, 6, 10, 20, 30],$$

$$Y2R = [-0.0000, 2.0000, 8.0000, 8.0000, 6.0000, 10.0000, 20.0000, 30.0000].$$

Consequently, it can be concluded that with the same accuracy of fit, a network with radial reference elements learns faster.

### 3. Conclusion

You can transfer the resulting trained SIS to the SIMULINK environment using the gensim(net) command, where net is the name of the SIS created. This will allow to use the trained SIS in more complex mathematical models describing the operation of aggregates and aircraft systems.

Thus, it is shown that neural networks are a powerful and affordable tool that can give reliable results in the technical diagnosis of systems and units of aircraft, working as part of the software information-diagnostic systems.

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