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S.S. Tovkach, Cand. Of Sci.(Engineering)
(National Aviation University, Ukraine)

Construction of neural networks of the aviation gas turbine engine drive

An approach of creation electrical aviation gas turbine engine, based on artificial neural network identification of mathematical model has presented. It can be effectively applied for development of aviation reducers and drives and its integrated control system. The design of the drive must ensure the operation of the engine in a wide range of modes from low throttle to maximum mode during the entire flight, including possible evolutions of the aircraft.

Introduction. Mechanical drives are widely used to ensure the functioning of aviation products and are divided into the following by purpose:

- drives of engine units, which ensure the functioning of the main engine systems, and aircraft units, which ensure their life support;
- drives of propellers and engine fans;
- drives of the main and steering propellers of helicopters.

To transmit the torque, change the frequency and the direction of rotation, all drives use gears interconnected by various kinematic schemes, the complexity of which depends on the requirements of the drive designs.

Propeller turbine engines (PTE) AI-24, AI-20, TP7-117 are built according to a two-stage coaxial kinematic scheme [1-8], in which the first stage is a differential one with three satellites, and the second one is a planetary one with a stationary carrier (overhead) with five intermediate wheels. Such a kinematic scheme is the most compact and energy-intensive, as the load is distributed over two flows.

The most promising gas turbine engine (GTE) drive is an electric drive with the advantages of low capital and operating costs; high energy performance in combination with high reliability and environmental friendliness.

At the same time, insufficient attention is paid to issues of system analysis of rational electrical systems of electrical GTE, ACS, monitoring and automation. Uneconomical unregulated systems with asynchronous and synchronous machines are still used for the electric drive of gas turbines. When working in the modes of regulating the gas supply and ensuring a smooth start-up mode, morally outdated and uneconomic methods of step control, bypass valves and hydraulic couplings, as well as reactor devices for starting units are used [2,3]. These devices solve only local tasks, not providing a complex of problems of energy saving, monitoring and automation of modern electrical GTE.

The goal of this research is the theoretical reasoning, development and research of power efficient systems of the frequency-regulated electric drive of the gas turbine engine, which ensure the implementation of intellectual control principles, operational diagnostics and predicting of the technical condition of the equipment based on the use of microprocessor tools and are distinguished by a comprehensive approach to solving the tasks of energy saving and automation.

Architecture of an automated artificial neural network of gas turbine engine electric drive. It can be considered two subsystems: 1) subsystem of receiving and processing information, which corresponds to the operation of EGTE with receiving data for technical state of synchronous engine and their further processing (distribution of data and estimation of variables); 2) subsystem of interpretation of the received information about the vehicle using artificial neural sstems (ANS) algorithms with fault recognition and recommendations for the implementation of its further actions (Fig. 1).

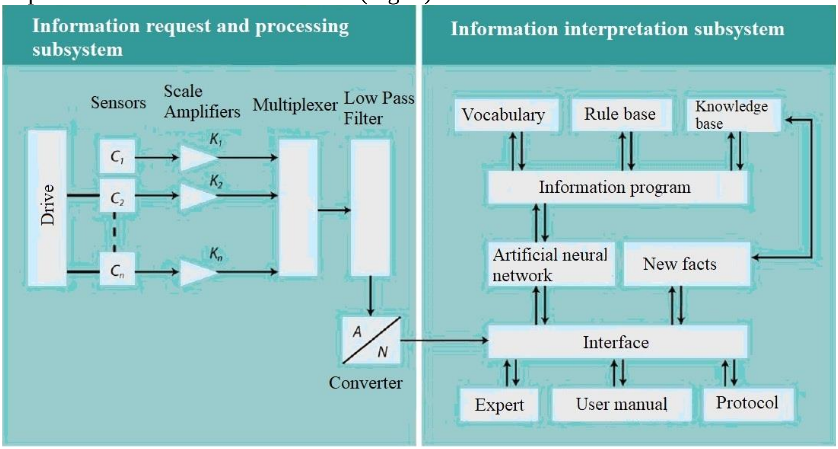

Fig. 1. Architecture of an automated artificial neural network of EGTE [1,4]

The order of construction of ANS [4,5]. The use of a large number of controlled variables (voltages, currents, FR and temperature of the stator windings) in the predicting of TS EGTE allows to increase the reliability of the monitoring procedure and make it more effective. To implement the ANN module, at the beginning, its dimensions are determined, that is, the number of its inputs and outputs (in our case, it is advisable to choose these values equal to 3 and 1).

Then the network architecture is formed based on the learning algorithm and minimization of the root mean square error of the monitoring results and prospects of predicting the TS of the SE with the determination of the residual resource.

Before embedding the ANN block (Fig. 1) into the subsystem of information interpretation, it is necessary to study the operation of three ANNs with inputs of different architectures. At the same time, the data inputs of the three ANNs are not of the same size, and, therefore, their structures, selected after the training phase, will differ and have a different number of internal layers and neurons in these layers. As a result of the selection of the most appropriate network of TS SE based on a volume parametric study of three ANNs, the following 4 decisions must be made.

1. Final selection of diagnosed variables. The most informative input variables characterizing the TS of the stator winding insulation are the temperature of copper, the intensity of FR and the level of overvoltages of the power supply network. This is due to the fact that, as shown by experimental studies in the natural conditions of various GTE, these parameters can adequately eatimate the TS and predict the occurrence of abnormal modes in advance. In addition, these variables are available for direct measurement by regular technical means and their direct representation in the neural knowledge base (NKB).

2. Construction of the NKB. In order to create a model based on ANNs that describes the operate and faulty state of the stator winding of the EGTE SE, it is necessary to create such an optimal design of the NKB, which would contain sufficient information about possible defects that occur in different modes of operation of the EGTE. To do this, based on the analysis of existing malfunction statistics (and simulation of possible malfunctions), all of them are grouped into 12 types (including healthy states), and for each state, the current changes of the three selected input variables during the entire measurement period are evaluated. As a result, the NKB of each variable was 3000 different values (vectors) characterizing the possible operating modes of the electric motor. This value, which corresponds to the number of measurements and the results of the set experiments, must be entered into the design of the ANN (table 1).

Table 1.

NKB construction

Failure type	Symbol	ANN code
Overheating in the groove part of the boring		000 000 001 001
Overheating at the terminals	QP	000 001 000 100
Overheating when starting the unit	UM	010 000 001 001
Synchronization output overvoltage		001 000 010 000
Overvoltage with rattling contacts	TZ	000 001100 000
Contamination with an oil-graphite mixture		000 100 001 000
Insulation defect in the groove part	TL	001 000 000 001
Insulation defect in the front part		010 001 000 000
No signs of insulation defects	QN	101 000 000 000

3. *Creation of a computer control unit*. The identified neural networks are multi-level with an optimal learning algorithm. To embed the ANN block in the VSMP SD, it is proposed to investigate 3 neural networks. After the phase of their testing and comparison with each other, you can choose the most suitable one for solving the entire complex of ANN forecasting tasks. At the same time, the stages of construction and suitability of neural networks are divided into three phases (Fig. 2). The first is related to the selection of inputs and the construction of the NKB, based on the files obtained during the analysis of all the mentioned three monitoring parameters. The second is related to the selection of network outputs (each separately) and its codes, and the third is related to the selection of network architecture.

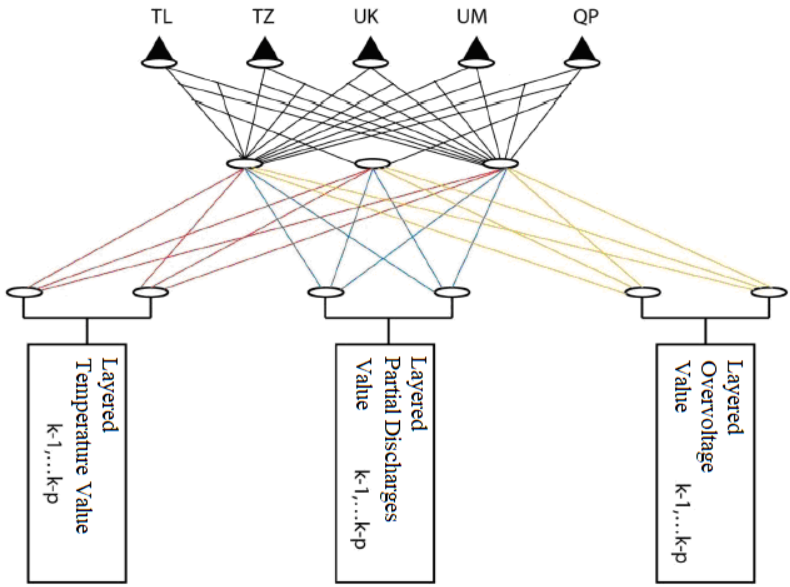

Fig. 2. ANS structure

4. *Definition of tests of selected networks.* With the number of used inputs of the ANN block equal to ten (in Fig. 2 $r = 5$) for each controlled variable in the table. 2 shows the obtained test results.

Table 2.

Test results

ANN	**The number of neurons**			
	Input layer	**Inner layer**	**Output layer**	**Root mean square error**
1	12	13	11	3,24221 e^{-15}
2	20	9	11	2,81314 e^{-16}
3	28	5	11	2,26580 e^{-17}

For the three networks, the selection step is performed after the second network completes its testing after 148 presentations of each example. At the same time, testing is performed in 2 stages: in the first, the network makes 100 repeated studies for each example of a faulty state, in the second - they are re-entered into the testing program, which stops after 48 iterations with a root mean square error of the test results equal to 3.7 Ve-16

Conclusion. During the study of EGTE monitoring systems, it is determined that:

- the heating of the windings in the middle part of the engine is 23 degrees higher than in the frontal parts, and the frequency of insulation breakdowns is more than 88%;
- the line voltage during the hours of observation can be 10.91 kV;
- "*online*" monitoring of the FR allows adequate evaluation of the EGTE technical state.

Algorithms for diagnosing and predicting the state of EGTE are implemented on the methodology and elements of fuzzy logic and artificial neural networks. On the basis of the fuzzy logic of Box-Jenkins and the Word network, when predicting the technical parameters of EGTE, more accurate results of the rapid processes of changing currents at the stage of model identification are determined. The rational choice of the EGTE vehicle predicting method is determined by the set of conditions, operating modes and system features of functioning.

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