Software-modeling complex for automation tests of low and medium power turbo electric tests

Boris Kavalerov¹, Grigory Kilin¹, and Evgeniy Zhdanovskiy¹*

¹Perm National Research Polytechnic University, Perm, Russia

Abstract: There are many problems connected with use of gas turbine units for electricity generation. The main problem is the gas turbine unit inefficient operation as a synchronous generator drive. To ensure the required quality of the generated electricity, which is largely determined by the nature of the transient processes of gas turbine unit, further improvement of control algorithms for automated control systems of gas turbine unit is required. In solving this problem, gas turbine unit should be considered in conjunction with other subsystems and units, for gas turbine power plants - this is, first of all, the electric generator and electric power industry in general. The process of tuning a gas turbine power plant control system is part of the test. Particularly time-consuming operations are manual tuning of the control system during experimental design and operational tests. Therefore, we propose to use a software-modeling complex, on the basis of which it is possible to obtain a neural network mathematical model of a gas turbine electro station and conduct its tests. In this case, in the process of testing the control system, the setup procedure is first performed on a mathematical model, then the settings obtained are checked using semi-bench testing, the final check of the decisions taken is carried out on a full-scale test bench, and data on the direct operation of a gas turbine power plant are also taken into account.

1 Introduction

Nowadays, the interests of the elaboration and development of sustainable electric power industry dictate the need to introduce modern methods of automatic control for power generating modules, which are often based on the ground use of aircraft engines. The bottleneck here remains the use of outdated approaches and outdated control system devices, which, as a rule, are based on a slight reconfiguration of aviation prototypes [1, 2]. As a result, the quality of the generated electricity in frequency and voltage suffers [3], this is due to the insufficiently efficient operation of the gas turbine unit (GTU) (Fig. 1).

In order to obtain an automatic control system (ACS) that would satisfy the quality indicators of power generation, it is necessary to conduct a large number of tests of the control object [4]. These tests can be carried out on full-scale test benches, but in this case, the list of possible operating modes is significantly limited, especially in the field of pre-emergency and emergency modes, in addition, the cost of testing is high. Tests of ACS controllers can also be carried out at full-scale stands using a mathematical model of a gas turbine electro station (GTES) in conjunction with an electrical system (ES). If a mathematical model is available, the procedure for setting the parameters of an ACS of a GTES is greatly simplified, since the direct operation of a real object is excluded. But in this case, high demands are placed on this mathematical model. The model should reproduce all the typical modes of operation of a gas turbine power plant, and it must also be fast-acting, for its direct use in the tuning circuit of GTU ACS regulators. The neural network model allows to obtain the required speed [11,12].

2 Methods

The article describes a software-modeling complex (SMC), which was specially developed to obtain neural network mathematical models of GTES in conjunction with the electric network for its subsequent use in setting
up ACS. The use of a neural network mathematical model of a GTES at the stage of scientific research tests leads to significant reductions in the debugging time of a GTES ACS at all subsequent stages of testing (Fig. 2). To obtain neural network models, the data of computer experiments were used, which were carried out on complex element-wise models of GTES and ES.

Fig. 2 – Test stages of ACS GTES

2.1 The structure of the software-modeling complex

The SMC structures and generalizes the obtained algorithms and models, as well as performs their software implementation. This software package allows you to get a neural network mathematical model of a gas turbine unit and an electric generator in conjunction with an external electrical system.

This SMC includes the following structural elements (Fig. 3):

1. Experimental data;
2. The module for obtaining mathematical models;
3. A set of mathematical models;
4. Module for checking the adequacy of the data of mathematical models;
5. Graphical display of data;
6. PID controller tuning module.

Fig. 3 – Functional diagram of the SMC.

Subsequently, the neural network models obtained using the software package are used to configure the parameters of GTU regulators.

Let us consider in more detail the two main modules of the SMC, responsible for obtaining the neural network model [8, 9] and setting up the GTU controller.

2.1.1 The module for obtaining a mathematical model

Artificial neural networks are widely used in various fields [10 - 24]. To construct a mathematical model of a GTES with an external ES, a recurrent neural network was used [8, 9] (Fig. 4).
The neuron model is as follows (Fig. 5):

\[
y_k = \varphi(v_k)
\]

(1)

\[
v_k = \sum_{i=1}^{n} w_{ij} x_i + b_k
\]

(2)

Where the output value of the neuron \(y_k\) is calculated by (1), and the receptive field \(v_k\) is found by (2).

As a result, in the presence of several layers, the output value of the neural network is calculated as follows:

\[
Y = \varphi\left(\sum_{k} w_{ok} \varphi\left(\sum_{j} w_{jk} \varphi\left(\ldots \varphi\left(\sum_{i} w_{kj} x_i\right)\right)\right)\right)
\]

(3)

Where \(w\) - the bond weight; \(x\) - the numerical value of the communication signal; \(\varphi()\) - the activation function of the neuron.

The main advantage of using a neural network is that you only need to specify the structure of the neural network. The model itself is obtained automatically during the learning algorithm [8, 9]. As the learning algorithm, the error back propagation algorithm was used, as the easiest to implement and time-tested [25, 26].

To obtain a neural network model, a training sample was formed based on several experiments. This sample was used to train the neural network and subsequently these data were sent to the neural network, and the results of the neural network were compared with the same training sample to determine model accuracy.

### 2.2 Adjusting controller parameters

Another important stage in the operation of the PMC, after the gas turbine electro station neural network mathematical model with an external electric power source was obtained, is to configure the parameters of the gas turbine controller based on this mathematical model. The stage of setting the parameters of the GTU controller is one of the two most important processes for obtaining the final result. Since the mathematical model is already ready, we can produce a sufficiently large number of experiments we need to achieve positive results. The controller tuning algorithm is shown in the figure 6.
It is this algorithm that underlies the procedure for setting the parameters of the GTU controller. As an optimization criterion, an integral criterion of the form is chosen:

$$j = \int_0^\infty \left[ e^2(t) + \tau^2 \cdot (e')^2(t) \right] dt$$  \hspace{1cm} (4)

where \(e\) is the deviation of the adjustable parameter from the set value, \(e'\) is the derivative of the deviation of the adjustable parameter from the set value, \(\tau\) is a constant having the time dimension [27].

This criterion minimizes both the deviation of the adjustable parameter and the rate of change of this parameter, reducing the oscillation.

In the version of the GTU for GTES, optimization is implemented according to the output coordinate - the rotation frequency of a free turbine. This strategy does not always give positive results, therefore, at least it is necessary to take an input coordinate - fuel consumption. Otherwise, the input variable, and with it the fuel consumption and speed of the turbocompressor, can be oscillatory in spite of a smooth change in the speed of a free turbine.

Accounting for several variables in the general criteria for automatic tuning of GTU ACS can be carried out by adding criteria for each variable individually with weighting coefficients [27].

### 3 Results and Discussion

Initial adjustment of the parameters of the studied regulator yielded unsatisfactory quality indicators in the form of a long transient time. During the operation of the PMC module, a mathematical model of a GTES with an external ES was obtained, based on this model new settings of the controller parameters were obtained, which led to an improvement in the form of a decrease in the transition time of the rotation speed of a free turbine (Fig. 7), obtained on a neural network model of PMC, then they were tested during the semi-natural experiments of GTU ACS.

Table 1 shows the adequacy measures of the obtained neural network model with respect to the primary experimental data after adjusting the controller parameters.

![Fig.6. Controller tuning algorithm](image)

![Fig.7. Change in the rotation speed of a free turbine](image)
4 Conclusions
The considered PMC is a powerful and useful tool for fulfilling the task of testing automation of GTES together with ES. An important advantage is the possibility of additional automation of some stages of the tests, which will positively affect the execution time of tasks. In addition, an equally important advantage of this PMC is the ability to obtain a high-speed mathematical model of a GTES and a power grid, that is, the model takes into account both the behavior of a GTU and the behavior of a synchronous generator together with a power grid. This feature allows you to configure the parameters of the gas turbine generator taking into account the dynamics of the electrical part of the gas turbine power plant. As a result, the estimated setup time for self-propelled guns during the tests is reduced by at least three times.

5 Acknowledgements
The study was carried out with the financial support of the Russian Federal Property Fund and the Perm Territory as part of the scientific project No. 19-48-590012.

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Table 1. Measures of adequacy.

| Free turbine rotation speed | Model Adequacy Measure |
|----------------------------|------------------------|
| Theil criterion            | 0.016348               |
| Pearson test (\chi^2)      | 1.552 (\chi^2 (0.05, 30) = 43.8) |
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