Development of Neural Network Diagnosing Models of Turbine Control Systems

Damir Kh. Imaev[1], Aleksandr M. Sinitca[2], Michail Yu. Shestopalov[3]
Saint Petersburg Electrotechnical University "LETI"
St. Petersburg, Russia
[1]damir.imaev@mail.ru, [2]amsinitca@etu.ru, [3]MYShestopalov@etu.ru

Sergej V. Kvashnin
Ltd “Sistema-Service”
St. Petersburg, Russia

***Abstract* — a hierarchical model of the process of neural network diagnosis of control systems of turbo-aggregates is proposed. Two levels of data processing consistently assess the degree of belonging of the symptoms to each of the potential faults and diagnose the technical condition. To accelerate the training of a neural network, a multi-stage training method is proposed. Using the example of a gas turbine control system, the efficiency of the proposed architecture of an intelligent diagnostic apparatus with a network of direct propagation and an LSTM network is analyzed.**

Keywords— diagnosis, neural networks, LSTM network, turbine, control system

I. Introduction

Diagnosis of technical objects control systems using expert models that diagnose based on threshold values of variables limits the amount of information used to analyze the state of the object. Using of time series as diagnostic features increases the amount of processed data about the analyzed object; however, direct transfer of expert knowledge to samples is a difficult task. As a compromise, it is proposed to use intelligent technologies (machine learning), in particular, neural network models [1] – [3]. Artificial neural networks, well proven in binary classification problems, are less effective in diagnosing problems, which associated with a multi-alternative classification.

It is proposed the approach to the development of neural network intelligent diagnostic systems with binary classifiers at the first level and the final classifier at the second level. The efficiency of the use of feed forward neural networks and recurrent networks such as LSTM [4] in diagnostic models of the first level is analyzed. As an object of research, one of the first models of turbine generator control systems, developed by W. Rowen [5], was selected to meet the demand for precise mathematical models of large-capacity gas turbines of General Electric.

II. Mathematical model of the control system

Structural diagram turbine control system [5] (Fig. 1) is somewhat simplified. The parameter values correspond to the model of a gas turbine of the GE 7001B type. Variables (except for temperature) are normalized with respect to nominal values. The range of applicability of the model is limited to a range of 95…107% of the rated speed of the turbine, outside of which the linear model of the turbine ceases to be adequate or discontinious control actions are possible.

The right part of the block diagram (Fig. 1) represents the turbine model: at the top there are blocks describing changes in the temperature of the exhaust gases and temperature measurements; In the center of the circuit there is a fuel subsystem, which includes a fuel valve, a compressor and a combustion chamber; In the lower part of the structural diagram, the equations of torque, rotational speed, load torque and fuel consumption are presented. The left part of the model contains a controller consisting of three components: speed control, temperature and acceleration. The last two components of the regulator perform a safety function; they prevent overheating or excessive acceleration of the turbine. Note, although the model of the turbine in the work is declared as linear, it contains a nonlinearity of the "minimum" type and a multiplication unit. Malfunctions of the exhaust gas temperature measurement channel can be both multiplicative and additive. Faults of the fuel feed channel are multiplicative (hard), which are modeled by a jump-like change of the corresponding coefficients of the equations, or "soft", which reduce to smooth changes in parameters. There are six classes of faults: hard and soft multiplicative malfunctions of the fuel system, hard and soft multiplicative thermocouple faults, hard and soft additive thermocouple faults. If the W. Rowen model [5] is supplemented with models of potential faults, and symptom detection and diagnosis devices are connected to the measured outputs, a diagnostic model [2] of the gas turbine control system will be obtained (Fig. 1)

III. Neuro network diagnostic model

Suppose the system can have N potential faults, i.e., taking into account an non-fault state, it is necessary to solve the problem of classifying the state set into N + 1 class.

A two-level architecture of the neural network is proposed. The first level consists of N independently trained subnets, which reveal the degree of belonging of the current state to the corresponding malfunction, i.e., symptoms.

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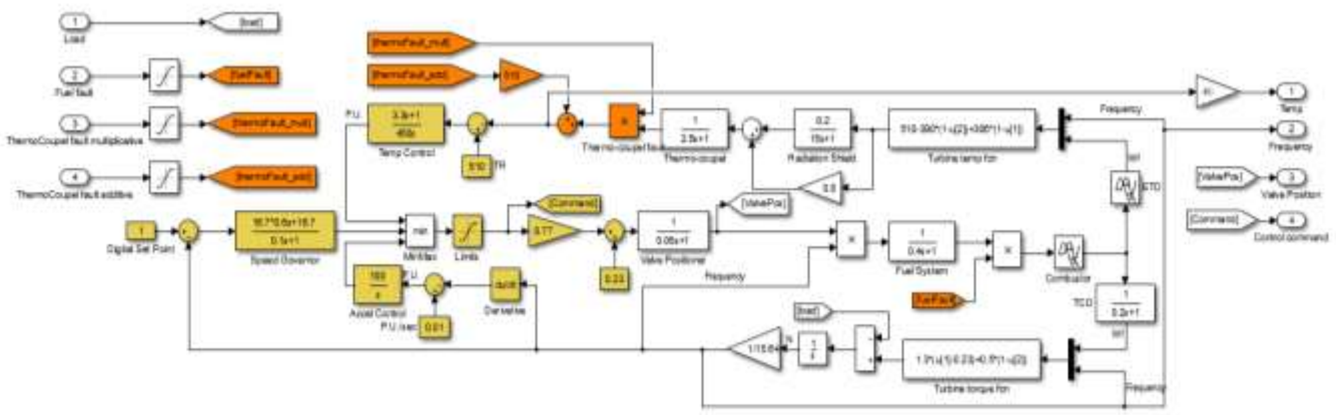

Fig. 1. Diagnostic model of the turbine control system

Trained independently neural networks can have intersections of classes of faults, forming a false positive affiliation to their class with input data corresponding to an unknown object state class. Despite this drawback, the training of a neural network in two classes is much simpler, which allows the use of relatively small feedforward networks. To compensate for the interference effect of the fault classes, a second level of the neural network is input, which inputs are the outputs subnets of the first level. Fig. 2 shows the structures of neural network diagnosis models with a feedforward network (Fig. 2, a) and the LSTM network (Fig. 2, b). Note that unlike the direct propagation network, where the input is a segment of the time sequence, the LSTM network, which is recurrent, has instantaneous values of the observed parameters at the input.

Neural network model of diagnosis is trained in several stages: at the first stage, the training of neural networks of the first level occurs and the values of their weights are fixed; on the next step, a complete neural network model is trained by adjusting the weights of the second-level network.

A. Preparation of data for the training of neural networks

Since the purpose of the diagnosis is to detect, localize and identify faults, including soft ones that reduce to relatively slow changes in the parameters of the object, then for the diagnosis it is necessary to use data on the behavior of the object in the form of time series.

To generate training data, the Simulink model of the turbine engine is used and specially created subroutines (m-files) are used to automate the preparation of training sequences. The processes of creation, training and testing of the neural network in Keras and TensorFlow [6] in Python are automated and with minimal changes can be used for other purposes of machine learning.

The following restrictions on the fault model are adopted: the intensity of hard faults (multiplier) belong to the range [0, 0.1], the intensity of soft faults is to the range [0, 0.01]. Thus, only those faults that do not lead to failures, stopping (accident) in the short term, and can be left undetected for a long time are considered. In addition, for a greater variety of data, the load moment of the turbine unit, the time of the failure and the intensity of the fault are taken at random values, different for each iteration of the simulation.

Computer simulation data are divided into blocks of 100 seconds (100 samples), corresponding to the use of feedforward networks to a group of inputs of 100 elements and 100 cycles of network operation – using a recurrent neural network, both during its training and during testing.

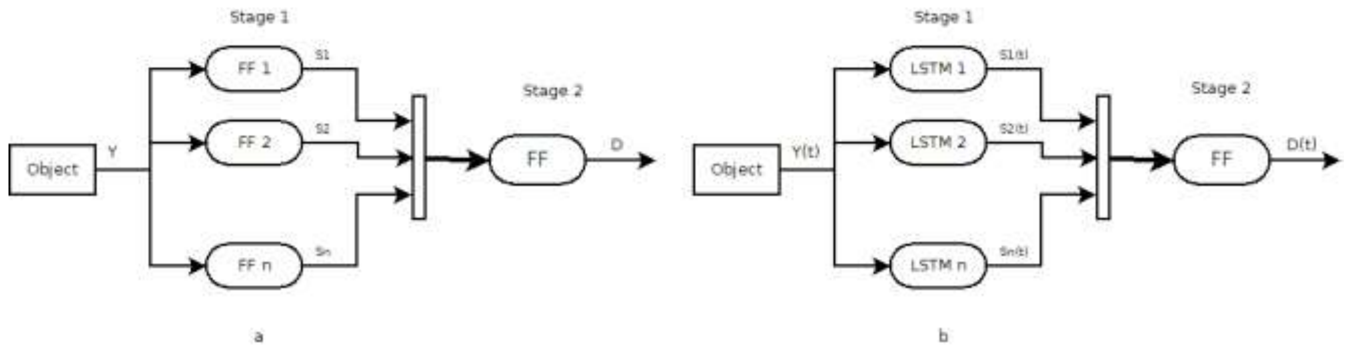

Fig. 2. The structure of two-level diagnosis a - feedforward network, b - LSTM-network

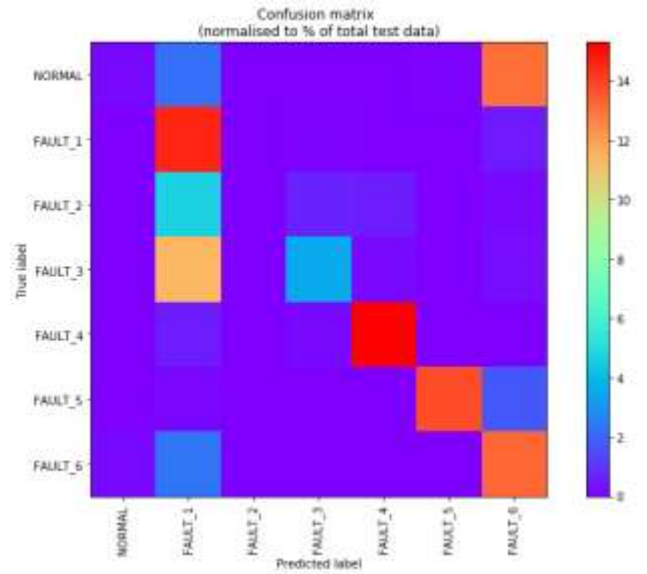

Fig. 3. Feedforward network confusion matrix

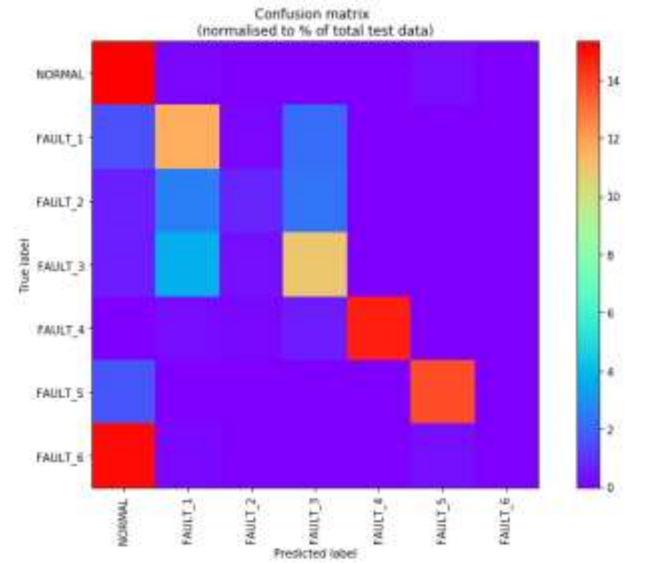

Fig. 4. LSTM network confusion matrix

B. Neural network training

First of all, neural networks are trained to identify the state of the object belonging to one of the classes of malfunction. Thus, the model is trained in N + 1 stages, where N is the number of faults considered. This approach allows achieving high classification accuracy at the first level of the classifier and almost completely eliminating false positives.

IV. Results of diagnostics of the control system of the turbo-unit

The main task of the research is to test the effectiveness of the proposed architecture of the neural network model and to select the most efficient type of neural network for the first level of the model. Proceeding from this, let us consider the quality of diagnosis for the two architectures studied, trained on samples of the same size. The key quality criteria is the accuracy of diagnosis and the proportion of false positives.

A. FF-network

Based on the results of training the neural network of direct propagation, when recognizing 6 types of faults of a CS with a gas turbine, an accuracy of 64% is obtained. In addition, the confusion matrix (Fig. 3) was obtained in the validation, the rows of which correspond to the true values, and the columns to the output of the network. The number of coincidences corresponds to the cells of the matrix. A good result of validation is the predominance of diagonal elements. In our case, showing the association of the classes of the working state of the system and the malfunction 1 – "Hard multiplicative malfunction of the fuel system". There is a significant number of false positive positives with diagnosis 6 – "Soft additive thermocouple malfunction" with a healthy control systen, which is probably due to the nature of the malfunction. Also there is a significant number of false negative diagnosis(considering the combination of a healthy state and malfunction 1).

Note that with the use of direct-spread networks of equivalent size, an accuracy of less than 17% is attained for direct diagnosis of all the turbine control system states considered.

B. LSTM-network

When training a recurrent neural network, advantages are evident at the first stage of diagnosis - the quality of the trained network is less sensitive to the choice of initial parameters, and greater accuracy of diagnosis is provided.

The accuracy of multiclass diagnostics when used as a binary classifier of the LSTM network was 67%. When analyzing the confusion matrix it is seen that there is a situation with class associations equivalent to the FF-network. In addition, when checking the efficiency of the LSTM network with a single-level architecture of the neural network diagnostics device, a similar accuracy of ~ 65% was obtained.

V. Conclusion

The proposed diagnostic architecture, using multi-level models with preliminary training on symptom detection sub-tasks, improves the efficiency and convergence of the learning process when diagnosed using feedforward networks. At the same time, it is not able to significantly improve the quality of diagnostics with respect to equivalent single-level models based on LSTM-networks. The training time of recurrent neural networks significantly exceeds the learning time of direct propagation networks, and the obtained diagnostic quality results are similar for a recurrent and direct propagation network using a two-level architecture, which makes it possible to talk about the advisability of further studies on the effectiveness of such architectures of diagnostic system.

Separately it is worth highlighting the fact of combining diagnoses in the classification, i.e., the use of only "raw" sensor data in the form of lengths of time series limits the quality of diagnosis. The stage of formation of diagnostic signs of higher categories is necessary. In particular, preprocessing the initial data to obtain frequency, cepstral and statistical representations.

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