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Research paper

Automated Prediction of Critical States of Turbogenerators During Thermal Expansion of a Rotor and a Stator Based on a Recurrent Neural Network

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Abstract

The present article is devoted to the development of a method and its software implementation for forecasting the critical states of a turbogenerator and its design elements that arise during starting-up & adjustment works and stopping a turbine. The method is based on a short-term prediction of the image of the spectrogram of vibrations during thermal expansion of the rotor and stator. The dependence of the increase in the vibration level in the spectrum with the failure of the turbogenerator design element is substantiated. The model takes into account the influence of thermal expansion on critical states. The technique of training a deep neural network is given in the classification of thermal influences on the level of vibration while a spectrogram receiving. For machine learning of a neural network in software, a recurrent autoencoder is used. The technique of operation is with a time sequence of spectrograms. To test the model is introduced the concept of semantic quality of clustering. Semantic quality, determined as the degree of correspondence between the information that can be extracted from the obtained cluster structure and the formalized presentation of the user. The interpretation of the results of the discovery of turbine generator defects is presented.

Keywords: *Turbogenerators, Rotor Vibrations, Vibrodiagnostics, Thermal Expansion, Thermal Influence, Forecasting, Critical State, Deep Machine Training, Neural Network, Recurrent Neural Network, Rnn, Heat Effects Assessment, Trouble Effects Evaluation, Troubleshooting.*

1. Introduction

Turbogenerators, Rotor Vibrations, Vibrodiagnostics, Thermal Expansion, Thermal Influence, Forecasting, Critical State, Deep Machine Training, Neural Network, Recurrent Neural Network, Rnn, Heat Effects Assessment, Trouble Effects Evaluation, Troubleshooting.

2. Methodology for Studying the Effect of Thermal Expansion on the Elements of the Turbine

The increasing of the level of vibration in the vertical, horizontal-longitudinal and horizontally-transverse direction negatively affects the elements of the turbine design. There is a danger of semi-dry friction on the shafts and bearings, the mutual fastening of the parts is disturbed, the rigid connection of the stators and bearings with the base plates is broken and the shafting becomes more and more misaligned.

Thermal expansion and, as a consequence, deformation, is an aggravating circumstance, which imposes strict requirements on vibration. In case of turbogenerator of block installations with a capacity of 150 MW or more, the vibration should not exceed 30 microns [1].

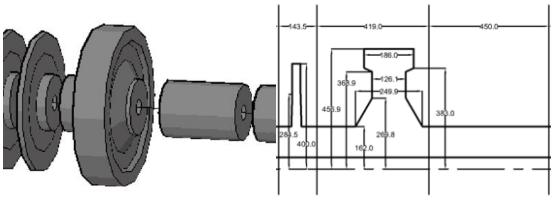


Fig. 1: The part of the high-pressure rotor of the turbine T-110

Consider the relative expansion of the rotor and stator in the axial direction. The rotor is connected to the cylinder through a thrust bearing. Therefore, the values of the relative expansion of the rotor and the stator do not depend on the position of the fixed point of the turbine [2].

In modern multi-cylinder steam turbines of TPPs and nuclear power plants, a rigid connection of the rotors is used. The thrust bearing, fixing the position of the shaft relative to the cylinder bodies, is usually located between the cylinders. This arrangement of the thrust bearing in the turbine makes it possible to reduce the relative expansions of the rotors and housings primarily in the most economical high-temperature cylinders and the absolute elongations of the shafts being accumulated along the chain of cylinders to either side of the stop ridge.

Among the criteria that determine the reliable operation of the turbine unit include such characteristics as the relative expansion of the rotor and the cylinder, the axial position of the rotor, the temperature difference between the upper and lower halves of the cylinder, and the absolute temperature expansion of the cylinders. All of them are controlled by special devices, and the maximum

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deviation of the axial displacement of the rotor causes the action of automatic protection stopping the turbine.

The peculiarity of heat transfer processes in a steam turbine is a high level of heat transfer coefficients from steam to walls and comparable (near) rates of heating of rotors and cylinder housings due to the small thickness of the walls of the body parts. These two circumstances allow the axial and radial clearances in the turbine to be small in size, which, on the one hand, improves the economics of the turbine installation, but on the other hand, it places high demands on the reliability of the operation of the turbine [3].

During the heating-cooling of the turbine, the rotors are elongated and shortened relative to the cylinders, since the heating and cooling of the rotors is faster than the cylinder bodies. The turbine rotors expand on both sides of the thrust bearing. Expansion of the cylinder shells during heating is strictly directed and directed along the axis by longitudinal fasteners.

The smaller the relative expansion of the rotor and cylinder, the more favorable it is for the turbine, especially for uncontrolled processes of changing the thermal state. This is one of the obvious criteria of turbine design quality.

The arrangement of temperature sensors on the outer housing allows one to determine in three sections the temperature difference between the upper and lower halves, and between the left and right sides of the housing. An emergency response specifies the case when the turbine is shut off by personnel without disrupting the vacuum with an increase in the temperature difference of the metal "top-bottom" above 35 ° C, "left-right" - more than 25 ° C. The mnemonic diagram of the turbine provides for signaling a rise in the vapor temperature of more than 284 ° C, a deviation of the vapor temperature of more than 284 ° C or less than 277 ° C, an increase in the temperature of the inner shell of more than 250 ° C. On the control panel, the warning and emergency temperature rise signals of the babbitt of the supporting and thrust bearings (75 ° C and 90 ° C), the inner casing (250 ° C) and the temperature of the exhaust pipes (60 ° C) are displayed.

In practice, the calculation of thermal expansion uses the properties of steel, which are linearly approximated by the method of least squares and are determined by the formula:

$$y = m \cdot T + b \quad (1),$$

where y is the desired expansion property, T [° C] is the temperature; m and b are the coefficients of linear approximation.

Determination of heat transfer coefficients is regulated [4]. In the model, the coefficients are taken to be constant for the elements (because the solution of the system is weakly sensitive to their variation within ± 30%), but there are no technical obstacles to use the variable coefficients in order to increase the modeling accuracy.

As a result of the simulation, one takes the average propagation velocity of the heat wave over the wall thickness equals 6 min. In this case, the temperature gradient along the thickness of the wall is not more than 0.5 ° C, that is, negligible.

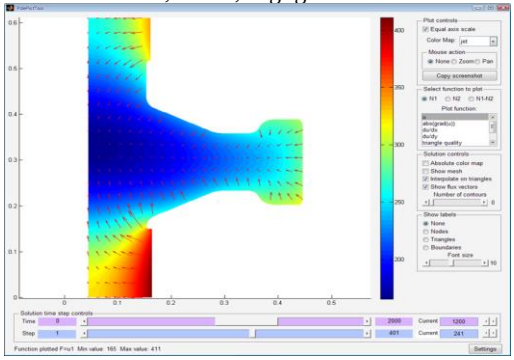


Fig. 2: A temperature field of the calculated region of the rotor

Schemes of thermal expansion of the turbine, the placement of fixed points and the location of thrust bearings have a great influence on the relative elongation of the rotors during the transients, on the axial clearances and forces, as well as on the deformation of the shells (housings). A justified solution to these problems, taking into account the new requirements for turbine maneuverability, is possible only if the temperature fields in the newly designed turbines are sufficiently accurately estimated, which is provided by modern knowledge in this field.

A consequence of the thermally unsteady state is also the appearance of a temperature difference between the top and bottom of the turbine housing when it stops. This temperature difference may also appear during start-up due to the accumulation of condensate in the lower points of the turbine casing with unsatisfactory operation of the drainage devices.

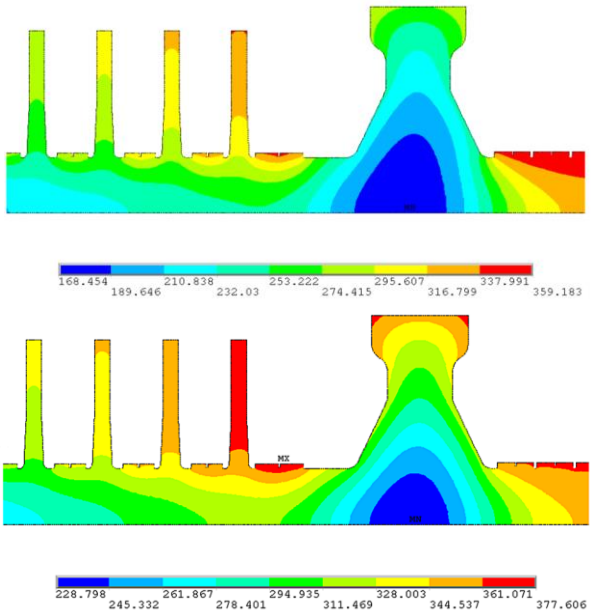


Fig. 3: Temperature field of the turbine T-110 / 120-130 at certain times: at the top - 20 minutes after the impulse of the rotor, at the bottom - 35 minutes respectively

The presence of a temperature difference between the top and bottom of the rotor leads to an upward bend, the more significant the longer the length of the rotor. The bending of the rotor leads to a reduction in the lower radial clearances in the seals, which may cause the rotor to touch the stator while rotating the rotor. Attaching the rotor to the ridges of labyrinth seals, in addition to triggering the crests, can cause local overheating of the shaft and, as a consequence, the thermal deflection of the shaft. With such deformations vibration occurs by changing the linear dimensions of the parts of the turbine [5].

A significant increase in vibration at critical speeds is caused by a significant imbalance in the rotor in its own forms of dynamic deflection of the shafts. As practice shows, this imbalance can be eliminated by special methods of balancing with bringing the vibration level of bearings at critical speeds to a value of the order of 30-50 microns. Therefore, the vibrational state of the turbine unit passing critical speeds with increased vibration cannot be considered satisfactory, even if the vibration of the bearings does not exceed the norm even at the working speed of rotation.

In units with a rotation frequency of 3000 rpm with a fundamental frequency of oscillations of 50 Hz, a high-frequency component of 100 Hz is most often detected, and low-frequency components with frequencies close to the lowest critical velocity of the "rotor-support" system (usually 17-21 Hz) or half the operating frequency (~ 25 Hz).

The presence of high harmonics, which are significant in amplitude, indicates the effect on the oscillating system of significant loads, which can several times exceed the loads that cause oscillations of the fundamental frequency. However, since

the question of the relationship between the spectral composition of the vibration and its danger to the turbine has not been sufficiently studied, we can confine ourselves only to the need to take more stringent tolerances for vibration in the case of significant high-frequency components.

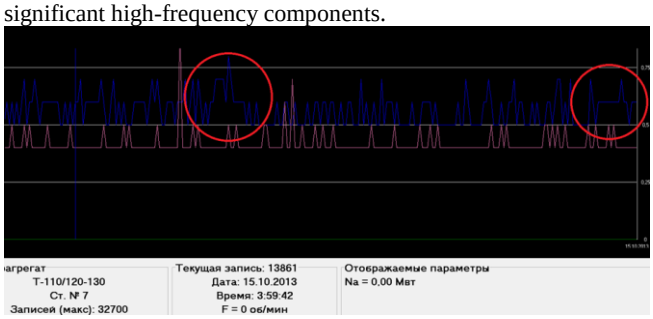


Fig. 4: Increasing the vibration of the rotor when it is imbalanced as a result of thermal expansion of the vibration measurement scale [aggregate, current record, displayed parameters; record (maximum), date, time]

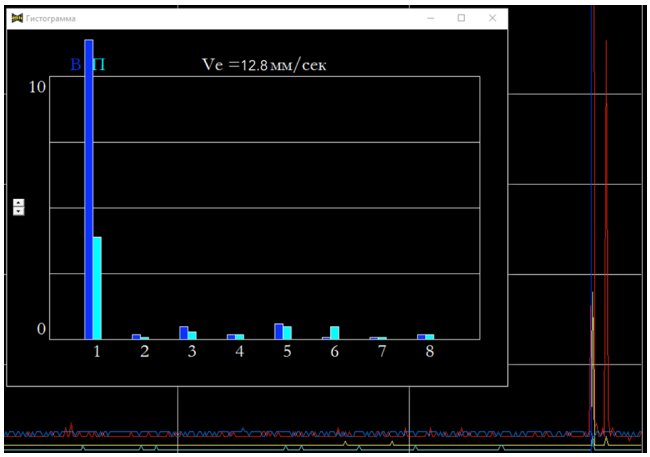


Fig. 5: Increasing the vibration of the rotor when it is imbalanced as a result of thermal expansion of the vibration measurement scale

As for low-frequency oscillations, then, because of their instability, their ability to suddenly and abruptly increase, they represent an undeniable danger to the machine. Therefore, if noticeable low-frequency components are detected in the oscillations of the bearings and rotors, the vibrational state of the turbine unit cannot be considered satisfactory.

3. The Result of the Use of Automated Software for Forecasting Critical Turbine States

The prognostic model of operation of the turbogenerator is based on the function of determining the reliability of the technical system. Considering the multicomponent nature of the technical system and the dynamic nature of internal and external factors, reliability can be defined as the ability of an object to predict, maintain stability, absorb impacts, respond, adapt and recover under undesirable effects or internal states [4].

In general, the forecasting agent is an algorithm for analyzing a discrete set of states in which our object can be located with the function of transition from one state to another [6].

The class of models successfully solving the regression problem is the convolutional neural network (Convolutional Neural Network, CNN) [7]. Convolutional neural networks belong to the paradigm of machine learning "deep learning", which has proved very well on various tasks. The principle of its use consists in the sequential application of convolution operations and selection of the maximum value (max-polling [8].

To obtain data on the forecast, the convolutional neural network should be checked in practice, estimating the possibility to solve the prediction problem on the basis of regression.

To train a neural network without a teacher, the convolutional neural network type, known as the "recurrent" auto encoder, is used (Figure 6). The main idea of auto encoders is automatic coding (as with compression, not encryption) information [9]. Recurrent auto encoders allow you to work with not one input vector, but a time sequence of vectors. The number of vectors in the sequence is specified by the num_steps parameter.

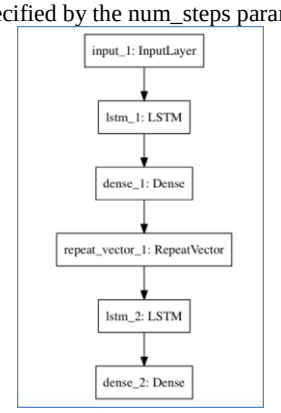


Fig. 6: Recurrent auto encoder for predicting the state of a turbo generator

The auto encoder consists of two parts: encoding and decoding.

The smallest layer is almost always average, in it the information is maximally compressed (encoded). Everything that is located up to the middle is the coding part, above the middle is decoding. In the middle is a layer that implements the modification of the code itself.

The encoding part is a LSTM recurrent network, at the output of which a vector in space is created with the dimension of latent_size. The number of neurons in the encoding network is set to hidden_size. If the learning is successful, this vector contains all the information necessary to restore the sequence. Therefore, this vector can be used for subsequent clustering of sequences to determine different operating modes.

The decoding part is also a recurrent net of the dimension hidden_size. At the output, a decoded sequence is formed, which should be close to the input sequence. The loss function is defined as the average of the sum of the error squares in the recovery of the sequence [10].

The input data are csv files with measurements taken from 8 points, each of which has 2 sensors. The sensors measure vertically and horizontally. For each direction the following indicators are measured:

Ve is the effective velocity, V1, phV1 is the amplitude and phase of the first harmonic, V2, phV2 is the amplitude and phase of the second harmonic, V_LF is the low-frequency vibration, V3, V4, ..., V9 are the harmonic amplitudes from 3rd to 9th, ADC-DC is a constant component of the ADC (analog-to-digital converter), V_HF is high-frequency vibration, SS is the spread of total vibro-displacements.

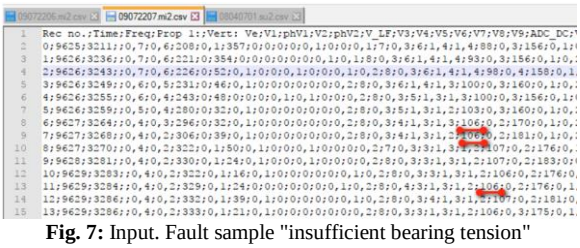


Fig. 7: Input. Fault sample "insufficient bearing tension"

Before learning, you need to create a configuration file or use a file with default values. To start learning a network with default values, you must run the following command:

stdbuf −o 0 python train.py 2>&1 | tee 1.log

If the configuration is specified in the config.cfg file, run the following command:

stdbuf −o 0 python train.py config.cfg 2>&1 | tee 1.log

The progress of training work is stored in the log_dir directory specified in the configuration and in the 1.log file specified at startup.
The loss function is evaluated on the training sample at each step and on the sample for validation at every 100th step.
After learning the network, the program saves the vectors of the hidden space for the validation sample in the latent_vectors.csv file.
Vectors have a dimension of latent_size, the default is 100. To visualize a multidimensional space, 2 techniques are used: analysis of the main components (PCA) and t-SNE [11].

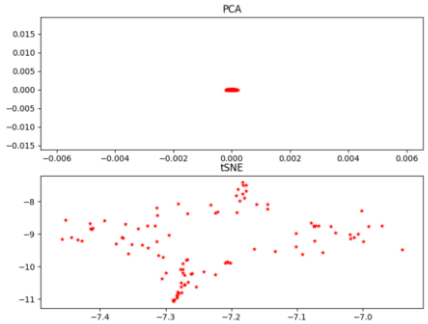


Fig. 8: Visualization of data vectors in a hidden space with the formation of vibration classes

4. Analysis of The Quality of Clustering

We introduce the definition of the semantic quality of clustering as the degree of correspondence between the information that can be extracted from the obtained cluster structure and the formalized user representation about the results of clustering. Thus, the focus of the quality assessment shifts from the definitions of certain properties of the set of vectors to the semantics of its content [12].
For each cluster, we set the measure of the similarity of the set of vibration acceleration Dvib, which is a measure of the similarity of two sets and is specified using the Tversky model:
$Dvib\ (A,B)=f(A \cap B)/(f(A \cap B)+ \alpha f(A - B)+ \beta f(B - A)\ ),\alpha,\beta \geq 0,$
where A and B are subsets of the vibration velocity measurements. Thus, from the value of Dvib (A, B), one can judge the degree of similarity of the resulting cluster structure to the formalized user representation of it, which, in accordance with the definition introduced, is the semantic quality of clustering [13].
When considering figure 7, four clusters with deviations from the norms can be distinguished. In two clusters, the proximity measure of Dvib for key representatives is clearly visible; the variance for each cluster will not exceed 0.2. Such clusters reveal groups of vibro acceleration on the spectrogram, which clearly indicate the effect of thermal expansion of the rotor.

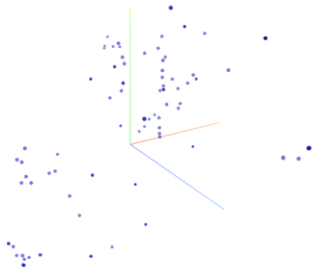


Fig. 9: Visualization of vibro acceleration vectors in a hidden space using t-NSE

In Figure 9, the vibro acceleration vectors are represented in a hidden space using t-NSE, and four main clusters corresponding to critical vibration states can also be identified on it. Two clusters closer to the center have data sets corresponding to vibrations associated with thermal expansion of the rotor.

5. Conclusion

Thus, an approach is proposed for forecasting the critical states of turbogenerators during the thermal expansion of elements and functional units during turbine start-up. For prediction, we used a time series analysis apparatus using a neural network of the recurrent autoencoder type. As a result, the neural network has learned to identify clusters with critical vibration states over a time period of more than 24 hours. When new data appear, the forecasting module will establish a data cluster with a dispersion of no more than 0.2 and determine the type of predicted malfunction, including those associated with thermal expansion.
This approach and methods have their limitations, the research of which can be the subject of further research and experiments.

Acknowledgment

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