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ANALYSIS OF FORECASTING AND MONITORING SYSTEMS OF ELECTRIC POWER EQUIPMENT

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ABSTRACT

Monitoring and forecasting the technical condition of power equipment is an integral part of technical diagnostics, which is intended to ensure the safety, functional reliability and efficiency of the technical facility, as well as to solve the problems of reducing maintenance costs and reducing the number of downtime losses due to failures [1]. The possibilities of monitoring systems in the energy sector are presented in a number of works (Leyserovich A. Sh., Kumenko A. I., Osika L. K., Chernetsky M. Y., Korshikova A. A. and D. R.). Different approaches to the assessment of the technical condition of energy facilities, prospects for the use of monitoring and diagnostic systems are shown.
In this article, the purpose of this article is to analyze the forecasting and monitoring systems of electric power equipment, as well as to test the measured and projected values during the operation of the monitor. At the same time, monitoring and forecasting systems of foreign and domestic manufacturers, methods of creating models of operation of power equipment are presented.

KEYWORDS

Smart signal, parameter, forecast, station, anomaly, algorithm, emission, graph, statistical, analytical, structural model, and regression.

Introduction

Smart Signal tizimi

The Smart Signal system is similarity-based modeling based on similarity-based modeling. The essence of this method is to calculate a similarity or similarity function for each parameter introduced into the model. If the parameter values differ from the model, then the similarity function for this parameter will be 0, and the specialist should pay attention to this parameter. In this case, the empirical model is described as a formula, that is, it exists in a definite form [1].
The system uses data from the monitoring object's ACS TP to create and analyze the model. The hardware performance model is based on archival data, since SBm is a statistically non-parametric method. To create the model, equipment performance data is used for six months or more with a frequency of one to ten minutes. The most favorable period for the construction of the model is considered to be already within one year.

The system has a ready-made library of equipment operating templates. There's also a library of simple breakdowns. Automatic fault detection occurs when the current fault matches faults in the fault library for different equipment groups.
Monitoring of equipment performance is done through fault analysis. The system compares the current readings of the sensor with the predictive value of the model, which describes the normal operation of the equipment. If the parameter values deviate from the model, the system will emit the appropriate message.
Figure 1 shows the interface for analyzing the behavior of parameters. It lists graphs of Active power, wind speed, and gearbox oil temp. Blue and green curves—the model and historical value of a parameter at the point corresponding to a given moment of time. Events are also recorded here—green, yellow, and white diamonds, red crosses, and green squares. Each sign and color denotes a specific type of event. For example, overcoming adhesions within defined limits, triggering an expert rule, or exceeding a parameter's technological parameter.
The main advantage of the generator is that their system is part of the ACS TP. However, system components can be used for equipment from other manufacturers.

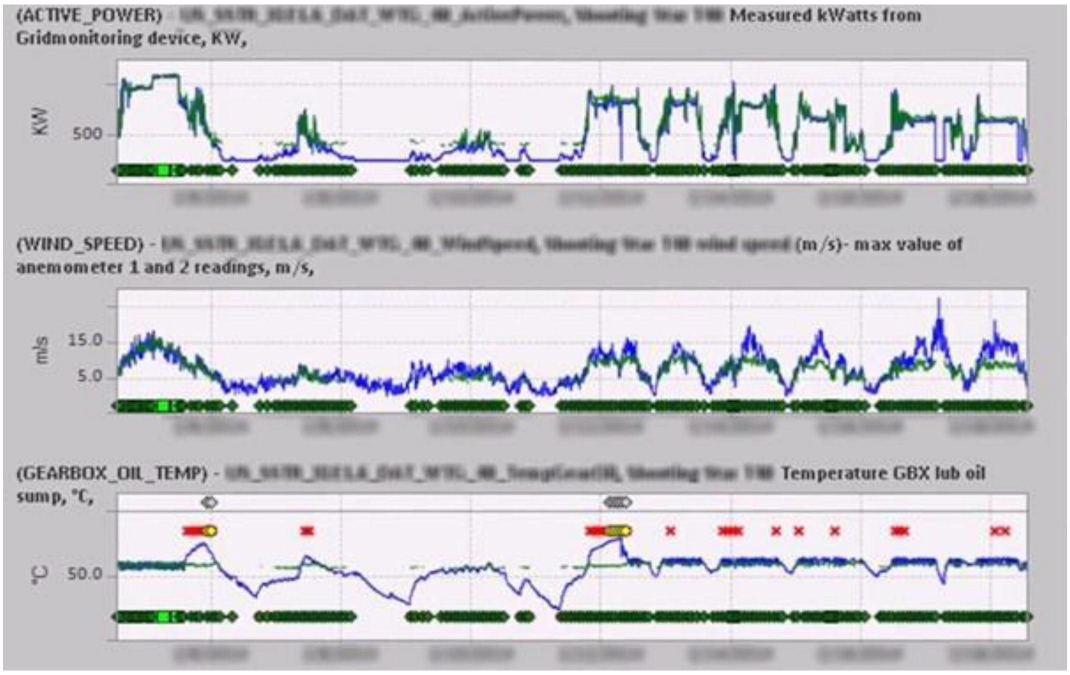

Figure 1. Work with graphics.

Anomalous monitor Siemens gas turbine technology

The system consists of two main components – the technology server and the license. The software consists of a set of functions, with its own license for each package. Thus the customer can configure the monitoring system the way he or she prefers. At the same time, the system is already fully integrated into the PTC ACS TP SPPA-t3000 starting with versions 4.2 and above. However, the system can be integrated into another ACS TP [2].
The system uses data from sppa-t3000 process server, but can use any OPC server. The user can create any number of models for various types of equipment. He can also change them at any time without any problem. All calculations are made on the technological server.

If the Anomaly Monitor is running as an installed application, i.e. in combination with the SPPA-t3000, all measuring points can be selected. The user can select the options from the list to build the model. In other cases, the archive parameters are read from a data source available to the technology server, e.g. via the OPC da/HDA protocol, and are displayed in a list similar to the installed solution. Each model is displayed in the form of blocks or automation functions.

In monitoring mode, the system compares model values and actual data. **The model value** is the expected value of the parameter, which is calculated in the sum of all sample values. In the case of neural networks, this computation is done in a "black box." In addition, the system calculates the difference between the actual and forecast values of the parameters, that is, it calculates the unbinded. Figure 2 shows the principle of detecting deviations in the operation of technical equipment. In well-trained models, the model values curve (blue curve) and the actual data curve (red curve) are almost identical when the model is converted to the data from which the model is built.

In zone 1, the gap between the model and historical value of the parameter begins. This is where the system signals a detected deviation in the performance of the controlled unit.

In Zone 2, the parameter crosses the technological threshold given in the ACS TP, where the station operator receives a signal from the ACS TP. The time frame from model deviation detection to triggering protection can range from several hours to several months, depending on evolving process dynamics. Previously, the response to deviations in equipment performance could prevent serious damage and predict repair work.

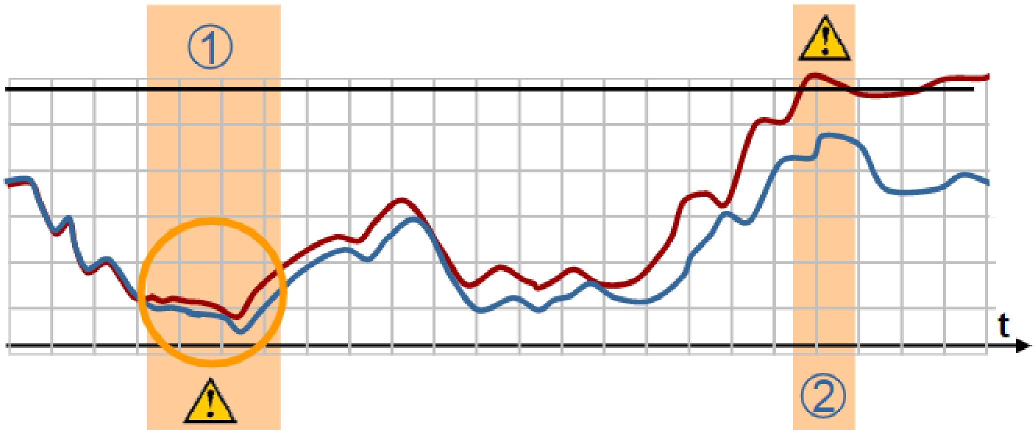

Figure 2. Schematic map of values measured and predicted during operation of anomaly monitor.

1 - Deviation from the behavior of the trained station was detected;

2-Normal operation of emergency settings as a result of a previously formed anomaly.

The system checks the signals for their reliability according to the following five algorithms:

1. *Testing for adhesion.* If a parameter does not change in a specific period, it is considered frozen;
2. *Check the parameter jump.* Jumps are determined by the emission of values that are above the parameter noise level (values of parameter change between the current and the previous one, which can be considered significant);
3. *Checking the signal for exceeding* the specified level (technological limit);
4. *Signal gradient testing* allows you to detect unusual gradual changes in the parameters of a continuous regression;

5. Checking the reliability of *sensor readings based on grouping*, i.e., interrelating parameter values with others. First of all, primary and backup sensors are checked in this way. If the readings differ between them, an appropriate warning is issued.

Thus, with the help of the system, verification of measurements is carried out. This approach avoids using data to analyze parameters that cannot be considered reliable.

Forecasting methods are the sequence of actions that must be performed in order to obtain a forecast model. Thus, the model is some formula that describes the operation process of a device that makes it possible to predict future parameter values. Universal predictive models are time-series models. They seek to find out whether future value depends on the past in the process itself, and calculate the forecast in that regard.

Time-series models can be statistical and structural. In statistical models, there are always external factors, the functional relationship between the known and future values of the time series, analytically determined.

Such models include regression and autoregression models, as well as exponential plane models. In structural models, functional dependencies are systematically established between external factors, known and future values of the time series.

Regression models Linear regression is the simplest model [6]. The model is based on a process that can be described by the following equation:

$$Y(t) = \alpha_0 + \alpha_1 \times X(t) + \xi_t \tag{1}$$

α_0, α_1 - model coefficients;

$\xi_t -$ A random error.

The regression model can be not only linear, but any other - polynomial, logarithmic [7]... [9]. More than one regression model that evaluates the relationships between parameters is most accurate. In this case, the model is usually linear because it is made up of additional terms, each of which is a predictor multiplied by the value of the coefficient. As a rule, a constant (free term) is also added to the model.

Regression models also include the Argument Group Accounting Method (MGUA). The essence of the method is the selection of regression models of optimal complexity. The more complex the model, the more accurate the forecast. It is often used when there is a lot of evidence in the specimen. In this case, the model is characterized by the following equation [10]:

$$Y(t) = w_0 = \sum_{i=1}^{m} w_t X_i(t) + \sum_{i=1}^{m}\sum_{j=1}^{m} w_{ij} X_i(t) X_j(t) + \sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{k=1}^{m} w_{ijk} X_i(t) X_j(t)\, X_k(t) + \cdots \tag{2}$$

Here is a set of free variables;$x = \{x_i = 1, \dots, m\}$

$w -$ vector of the parameters of the coefficients of weight.

Equation 2 is called the reference function. Models are constructed for all or selected evidence. Each model has a weight ratio, the best of which is chosen at the next stage. If the quality of the models found and the predictive values derived from it are satisfactory, then the process will stop. Otherwise, the models selected in the previous step will be used as $X_1(t)$ ... $X_n(t)$the argument.

The advantage of regression models is their simplicity, speed of achievement, availability of intermediate calculations, and heterogeneity of the problems to be solved, making these models applicable to all fields. In addition, they have the following disadvantages:

- Low forecast accuracy for interpolation data;
- the complexity of determining the type of functional dependence;
- complexity of defining parameters;
- Subjective choice of model (dependence). Formally—adaptation to empirical material.

Conclusion

This article analyzes the performance of power equipment, as well as the forecast of its technical condition. The easiest and most understandable regression analysis methods for experts to implement for prediction. The method of group consideration of arguments is the most complex of them. In addition, it requires a lot of computational resources, but its undoubted advantage is seen in the accuracy of the forecast. In recent years, neural networks have become popular for prediction. The most common ways to analyze the performance of power equipment are similarity-based modeling methods and neural networks.

For prediction problems, simple linear regression is most commonly used. In fact, it gives inaccurate forecasts because it does not take into account the peculiarities of regulation, changing regimes, etc. Neural networks and complex regression models predict more accurately, so it is preferable to use them.

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