Research Article

An expert neural system for diagnostics of motor-driven valves[*]

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Abstract

Trouble-free operation of motor-driven valves (MDV) is one of the key factors behind the operating safety of NPPs. As critical components, MDVs are a part of a safety system and a safety-related system. This imposes the highest possible requirements on the MDV reliability.

MDVs are the most numerous category of the NPP components. Depending on design, one power unit contains 1500 to 3000 motor-driven valves alone. It follows from an analysis of the NPP failures that many of these are caused by failed motor-driven valves of safety and safety-related systems.

The paper presents a description of an automated system for diagnostics of shutoff and control MDVs used in the NPP pipelines. The developed diagnostic algorithms make it possible to take into account the variability of the MDV technical parameters, while taking into account, at the same time, rated restrictions on diagnostic parameters, if any.

Keywords

Introduction

In the process of operation, MDVs are exposed to impacts from a large number of factors, infrequently of a random nature, e.g. variation of the fluid and environment parameters. The higher is the variation of the technical condition parameters, the less efficient are the maintenance and repair routine charts, since, in this case, there is always a factor of uncertainty regarding the technical condition of the respective item. Therefore, despite regular preventive maintenance activities, not all MDV defects can be detected on a timely basis.

The paper presents a diagnostic system which allows fully automated online diagnostics of MDVs at early stages of the failure development. The developed diagnostic algorithms make it possible to take into account

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the variability of the MDV technical parameters and rated limits for diagnostic parameters if any. An overview of the typical MDV failures is provided in (Adamenkov 2009, Slepov and Sysoyev 2014).

Terms and definitions

The paper uses the terms as specified in methodology (MT 1.2.3.02.999.0085-2010) "Diagnostics of Motor-driven Pipeline Valves." approved and put into effect by JSC Concern Rosenergoatom's Order No. 9/270-17, dated 27.03.2012.

Methodology (MT 1.2.3.02.999.0085-2010) defines the requirements to the content and organization of activities to evaluate the technical condition of motor-driven shutoff, shutoff and control, and control valves installed in the process systems of NPP units using diagnostic tools and methods.

The methodology's requirements apply to valves of safety class 2, 3 and 4, as qualified in NP-001-97 (PNAE G-01-011-97), and of groups B and C under PNAE G-7-008-89 developed as required in NP-068-05, OTT-87, as well as developed prior to OTT-87 was put into effect.

According to (MT 1.2.3.02.999.0085-2010), the paper uses the following terms with respective definitions:

- active power – a quantity equal to the root-mean-square value of the dipole instantaneous power for a particular period (GOST R 52003);
- diagnostic (monitored) parameter – a parameter of the item used for its diagnostics (GOST 20911);
- cyclogram – a time series (current, voltage, active power, etc.) which describes one MDV opening or closing cycle.

Description of the diagnostic algorithm

Initial data

The experience of the MDV operation and an analysis of the electrical machine failures show that the motor current and/or active power signal measured for one or three phases is informative enough for identifying the technical condition type (serviceability evaluation) for the CHP plant or NPP unit process system valves (MT 1.2.3.02.999.0085-20103). The recorded information for the calculation of diagnostic parameters is electrical parameters of the motor stator winding current and voltage.

The motor (three-phase) stator winding and limit switch current and voltage signals are recorded in real time by measuring modules in the cabinets of the unilateral-maintenance three-phase distribution assembly for gate valves (RTZO) to the database of the data acquisition system. The architecture of the data acquisition system is described in (Matveyev et al. 2009).

The MDV diagnostics based on signals of the motor current consumed in the process of the opening and clos-

ing operations is considered (Matveyev and Skladnikov 2009a, 2009b, Abidova et al. 2015).

Active power cyclogram

The active power cyclogram calculated based on the current and voltage signals using the formula below plays the key role in diagnostics of failures

$$P(t) = \frac{1}{T} \int_{t}^{t+T} u(\tau) \cdot i(\tau) d\tau, \qquad (1)$$

where T is the carrier frequency period (50 Hz); and $u(\tau)$, $i(\tau)$ are the instantaneous voltage and current values at time τ respectively. An example of the active power cyclogram is provided in Fig. 1.

Further, diagnostic signs are identified in the active power cyclograms based on which a conclusion is made as to if there is a defect.
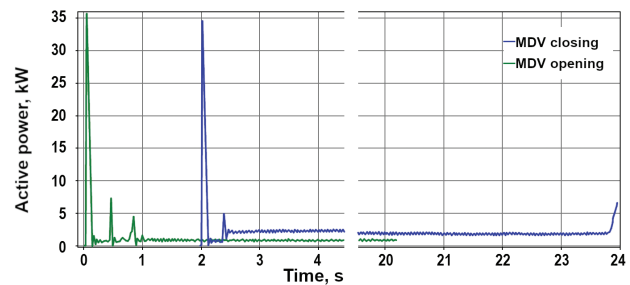

Figure 1. Active power cyclogram.

Diagnostic system operation algorithm

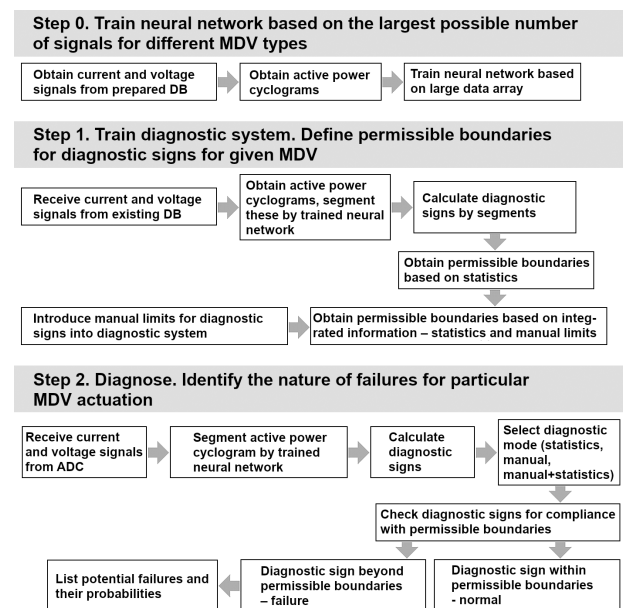The diagnostic system operation algorithm is presented in Fig. 2.

Figure 2. Diagnostic system operation algorithm.

Procedures to obtain diagnostic signs

Segmentation of the active power signal

The key idea behind the proposed approach is segmentation of the active power cyclogram with the diagnostic signs identified further by segments (Fig. 3).
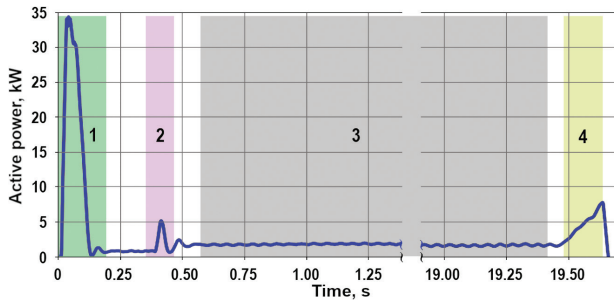

Figure 3. Segmentation of an active power cyclogram: 1 – motor start (roll); 2 – gate shift (for opening); 3 – gate moving; 4 – gate sealing (for closing).

A distinctive feature of this approach is that segmentation is fully automatic and uses a pretrained neural network of the U-Time type (Perslev et al. 2019) (a convolution network adapted for segmentation of time series and built based on the encoder/decoder principle using skip-connections, that is, components which connect the decoder and encoder parts in each scale). Such description of the network architecture and the evidences to prove its efficiency as applied to segmentation of the active power signal are presented in (Kotsoyev et al. 2021).

For each time point of the active power cyclogram, the neural network predicts the probability of any given segment. Therefore, one can state after a set of the active power cyclogram points is selected, the probability of a segment for which is close to unity (e.g., of over 0.95), that these points relate to the selected segment and define its boundaries (Fig. 4).
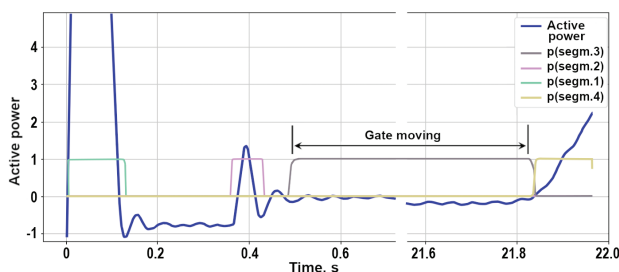

Figure 4. Result of the active power cyclogram segmentation. The probability of each segment p(segm. N), $N \in [1, 4]$ has been obtained by a neural network.

The neural network is trained on a large array of MDV signals (cyclograms), not necessarily for any particular type of valves, both based on opening and closing signals, and on shutoff and control MDVs. The so trained neural network is capable to segment any "relatively similar" MDV signal.

In the process of training, the entire array of training data is broken down into data properly, on which the training is based, (training sample) and data for checking the quality of the trained network operation (validation sample).

As shown in (Kotsoyev et al. 2021), the network trained based on a training sample of 500 cyclograms identifies segments based on a validation sample (150 cyclograms) correctly in the following percentage ratios:

- segment 1: 98.28%;
- segment 2: 92.60%;
- segment 3: 99.73%;
- segment 4: 71.65%.

Therefore, the neural network training shall not necessarily be undertaken each time for each particular MDV. Training based on a large set of 'similar' data is enough, and it is also possible to use an earlier trained network. With an unsatisfactory quality of segmentation, the network should be trained additionally on the signals of the given MDV.

Identifying the set of diagnostic signs

A set of diagnostic signs is identified for each segment. Information calculated based on current signals (by phases) and Fourier spectra from active power and current signals are used along with the active power signal.

The results in (MT 1.2.3.02.999.0085-2010, Abidova et al. 2016b) were taken into account when determining the set of diagnostic signs.

According to (MT 1.2.3.02.999.0085-2010), the following characteristics are extracted from the cyclogram in the process of the MDV diagnostics:

- opening (closing) operation runtime, s;
- difference in the opening and closing time, absolute (sec) and relative (%);
- opening (closing) gate moving current, A;
- opening (closing) gate moving power, kW;
- opening (closing) gate moving time, s;
- ratio of the startup current value to the working current value (the startup power value to the working power value) in the opening (closing) moving;
- ratio of the gate shift current (power) to the working current (power) in the course of the opening operation;
- ratio of the gate sealing current (power) to the working current (power) in the course of the closing operation;
- gate shift smoothness in terms of the current signal (active power signal) during opening (closing);
- coefficient of divergence in the current (active power) values in the limits of the opening and closing operation runtime boundaries;
- motor startup time interval, s;
- shutoff gate sealing time during closing, s;

- motor shutdown time at the opening and closing operation end, s;
- shutoff valve gate shift time during opening operation, s;
- working current (voltage) asymmetry in phases *A*, *B* and *C*;
- amplitude of the harmonic matching the motor output shaft speed.

The above diagnostic signs are identified by segments (its own set of diagnostic signs is prepared for each segment).

Stochastic characteristics of cyclograms (such as entropy) were investigated in (Abidova et al. 2016b) depending on the extent of the defect manifestation. The connection of Shannon entropy to the MDV state was shown theoretically in (Abidova et al. 2016b) and a higher sensitivity of Shannon entropy with respect to individual defect types was shown.

In this connection, such characteristics as Shannon entropy and interchange entropy were selected as diagnostic signs (in addition to those listed above) (Abidova et al. 2016a).

Both entropies characterize the variability of the process. Additional harmonics occur in the signal and the variability grows as the item condition deteriorates. The Shannon entropy increases and the interchange entropy decreases as the variability grows (Chumak 2011).

A connection is shown in (Khegay 2017) between the entropy indicators and the nature of the MDV failure (electrical or mechanical component failure).

The following diagnostic signs were calculated for each segment.

Segment 1 (motor start and roll):

- peak width at half height;
- segment maximum;
- sum of squared deviations from the rising edge linear regression.

Segment 2 (shutoff valve gate shift, for opening):

- peak width at half height;
- segment maximum.

Segment 3 (damper movement):

- average distance between the upper envelope and the lower envelope (for maximums and minimums) in terms of active power;
- spectral entropy;
- Shannon entropy;
- interchange entropy;
- working current value by phases;
- working current asymmetry;
- gate moving smoothness (for current) by phases (for envelope, Hilbert);
- current smoothness difference by phases;
- spectrum amplitude.

Segment 4 (gate sealing, for closing):

- segment maximum;
- slope angle (linear regression);
- sum of squared deviations from the segment linear regression;
- distance between the maximum and the minimum.
- Shared characteristics according to the cyclogram:
- ratio of startup power to gate moving power;
- ratio of crack power to gate moving power;
- ratio of gate sealing power to gate moving power;
- ratio of startup current to gate moving current;
- ratio of crack current to gate moving current;
- valve final action time;
- crack detector;
- gate sealing detector.

This set of diagnostic signs is not final and may be changed by the operator (the operator is in a position to decide that any of the signs are insignificant for diagnostics of the given MDV or 'switch' them off).

Permissible boundaries of diagnostic signs

With a database available for the particular MDV, the trained neural network segments each cyclogram and diagnostic signs are identified further by segments. Assuming that most opening and closing operations take place normally (there are no multiple critical failures and the valves are in operation on the whole), it becomes possible to determine the permissible intervals for each diagnostic sign based on the accumulated statistics (using 0.25-quantile Q_1 and 0.75-quantile Q_3, Fig. 5). Single 'defective' actuations are screened off automatically.
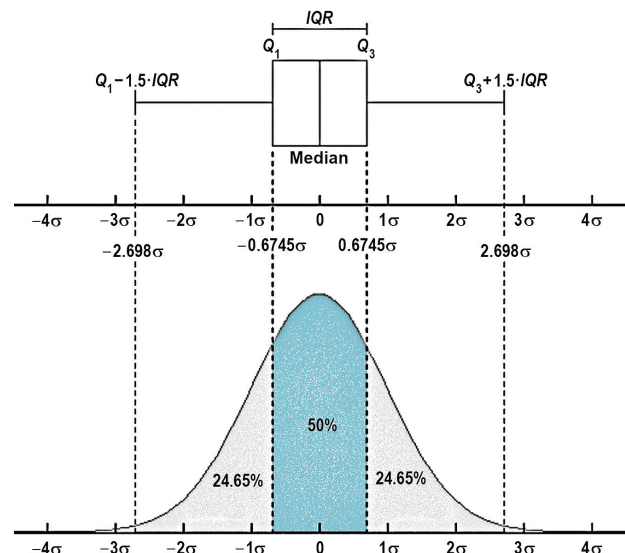

Figure 5. Quantiles of distribution obtained for each diagnostic sign.

The diagnostic system includes a manual mode of defining tolerances for diagnostic signs which is important with no sufficient statistical data when these boundaries
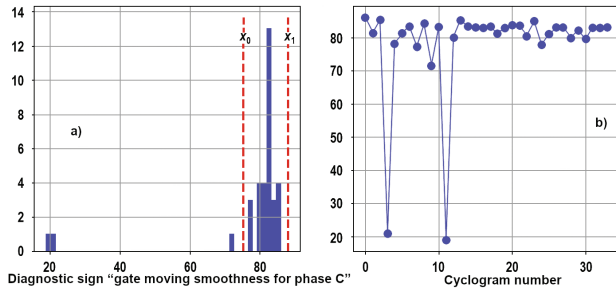
Figure 6. Diagnostic sign "gate moving smoothness for phase C": a) – histogram, $x_0 = 75.32$ and $x_1 = 88.06$ – left-hand and right-hand permissible boundaries for quantiles; b) – diagnostic sign value based on the closing cycle statistics for one and the same MDV.

are fixed in the MDV datasheet. The operator is in a position to define the permissible intervals manually and then choose the operating mode: statistics alone, statistics with manual limits, or manual limits alone (e.g., the valves are new and there is no statistics so far).

The cyclograms, the diagnostic signs for which are beyond the permissible intervals, are identified as a 'defect'.

An example of determining the permissible intervals based on statistics is given in Fig. 6 for the diagnostic sign "gate moving smoothness for phase C". The diagnostic sign "gate moving smoothness", γ, is calculated for segment 3 as

$$\gamma = \left(1 - \frac{I_{max} - I_{min}}{I_{med}}\right)\cdot 100\%, \qquad (2)$$

where I_{max}, I_{min}, I_{med} are the greatest, the smallest and the median values of the signal current envelope.

According to (MT 1.2.3.02.999.0085-2010), value γ of below 75% is treated as a fault condition.

Cyclogram analysis and diagnosis generation

After the permissible intervals are determined for diagnostic signs, the diagnostic system is capable to generate the diagnosis for each particular cyclogram.

Diagnosis is made in accordance with Appendix P to Methodology (MT 1.2.3.02.999.0085-2010). The appendix lists the potential defects for each MDV component and describes how the defect manifests itself through the cyclogram characteristics.

The neural system segments the cyclogram obtained and identifies the diagnostic signs by segments. If all of the identified signs are within the permissible intervals, such signal is defined as "normal". If one or more signs are outside the permissible limits, the "failure" is detected and the identified failure and the potential MDV defect are compared in accordance with (MT 1.2.3.02.999.0085-2010) (Table 1).

Taking into account that several signs can simultaneously indicate to the same failure (e.g., being simultaneously outside the permissible boundaries are the following signs for segment 3: "working current asymmetry", "gate moving smoothness (in terms of current) for phases (for envelope, Hilbert)", "spectrum amplitude", or for segment 4: "segment maximum", "distance between maximum and minimum", which indicate the same defect ("No sufficient lubricant or lubricant contamination in the motor drive gear box"), the notion of defect "repeatability" was introduced. The defect repeatability is the higher, the larger is the number of signs which indicate the given defect (among the overall number of signs being outside the permissible limits).

An example of the diagnostic system display is given in Table 2.

Conclusions

A prototype of the automated MDV failure detection system has been developed and deployed.

The developed system allows rapid online diagnostics of the MDV operation which increases greatly the probability of defects to be detected at early stages without

Table 1. Example of comparing the cyclogram characteristics and diagnostic signs

Defect	Manifestation in cyclogram	Diagnostic signs
Motor output shaft beat	Opening/closing takes more time than rated	**Shared characteristics** according to cyclogram: valve final action time
	Gate moving smoothness less than normal (equal in all three phases)	**Segment 3:** gate moving smoothness (in terms of current) for phases (for envelope, Hilbert); current smoothness difference for phases
No sufficient lubricant or lubricant contamination in the motor drive gear box	Gate moving smoothness less than normal (equal in all three phases)	**Segment 3:** working current asymmetry; gate moving smoothness (in terms of current) for phases (for envelope, Hilbert); spectrum amplitude
	High torque during valve closing	
	Startup current much in excess of working current	**Shared characteristics** according to cyclorgam: ratio of startup current to gate moving current; valve final action time
	Opening/closing takes more time than rated	**Segment 4:** segment maximum; distance between maximum and minimum
	Motor high-load operation	
Motor winding damage (defects)	Working current and voltage asymmetry in phases (phase unbalance over 10%)	**Segment 3:** working current asymmetry
Motor malfunctions	Startup current much in excess of working current	**Segment 1:** peak width at half height; segment maximum; sum of squared deviations from rising edge linear regression
	Long motor starting time	
	Working current greater than rated	**Segment 3:** working current value for phases
	Opening/closing takes more time than rated	**Shared characteristics** according to cyclogram: ratio of startup current to gate moving current; valve final action time

Table 2. Example of diagnosis for a signal cyclogram

Failure	Repeatability
One-sided wear in MD worm gear pair	25.00%
No sufficient lubricant or lubricant contamination in MD gear box	25.00%
Motor output shaft beat	18.75%
Wear of the gear box kinematic pairs, teeth breakdown in MD gear assemblies	18.75%
Increased "waviness" of active power. Deviation from the value typical of given valve	6.25%
Motor stator winding fault	6.25%

waiting for critical failures, to make it possible to update the equipment repair schedules and reduce the repair costs, and to avoid sudden breakdown of equipment.

The system allows flexibility of adjustment for the given MDV type, and makes it possible to take into account both rated limits for the valve parameters and the fluid effects in the NPP piping. The operator can define his/her own set of diagnostic signs which describe as fully and accurately as possible the operation of the given MDV.

Automation of the segmentation process excludes the human factor effects and makes it possible to analyze the statistics of the MDV actuations, find trends in the diagnostic sign changes and predict the deterioration in the valve condition.

The aforesaid allows increasing greatly the reliability of the MDV failure detection and making the diagnostics fuller and more target-focused.

As a result of testing the operation of the developed diagnostic system, the listed valve failures coincided with the listed malfunctions identified as part of the offline diagnostics for the Integrated Valve Diagnostic System installed at unit 6 of the Novovoronezh NPP.

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