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Vibro-forecasting of fault development in hydropower units

Proposed in the paper are the mathematical models and algorithms for vibroforecasting of fault development in hydropower units, such models and algorithms being based on the spectral analysis of vibration signals. With real-world vibroacoustic signals being of purely non stationary nature, i.e. their spectr a varying with time, the authors proposed to carry out spectral analysis using discrete wavelet transformation resulting in acquisition of three-dimensional amplitude-frequency-temporal spectrum in the form of wavelet coefficient matrix. It should be noted that, due to an exceptional complexity of the hydropower unit as a dynamic hydroelectromechanical system and practical impossibility of mathematical description of dependence between the vibroacoustic signal and all factors that cause vibration, it makes sense to treat the hydropower unit as the «black box», that is to simulate its external functioning rather than its structure. That is why, for the purposes of forecasting of fault development in hydropower units, generation of three-layer artificial neural-like network is stipulated. Such fore casting is based on analysis of trends in wavelet coefficients in each of frequency bands of vibroacoustic signal's amplitude-frequency-temporal spectrum. Further on, stipulated is the breakdown of these trends into vibration signals' components (background, hydrodynamic, electrodynamicetc.) that correspond to particular factors that cause vibration. Processing of these components allows determining there sulting prognostic conclusion with regard to fault development in hydropower units as avariety of values representing the probability levels of different vibration factors. Besides, the paper contains an example of such prognostic conclusion obtained on the basis of historical values of vibroacoustic signals obrained from vibration monitoring subsystem of DnestrHPP-2.

Keywords: vibroacoustic signal, discrete wavelet transformation, wavelet coefficients, artificialneural-likenetwork, frequency band, probability value.

Introduction

Development of renewable power sources, with hydropower industry being one of its development sourses, forces us to pay particular attention to safe operation of hydropower plants (HPP). Emergencies athigh-powerHPPs that took place ininprevious years (Tajikistan — 1983, Russia — 2009, Switzerland — 2000, USA — 2005, India — 2013, Kyrgyzstan — 2015 and 2016) led to huge property damage and even fatalities.

That is why timely diagnostics and particularly forecasting of hydropower units' faults are of great significance. Vibration diagnostics is one of the most widespread diagnostics types, since vibration signal's almost instantaneous reaction to change in equipment condition is a very important property in case of an emergency, when the speed of diagnosis establishment and decision making is a determinant factor.

Vibration diagnostics is a discipline that comprises theory and methods for arrangement of processes associated with identification of machines' and mechanisms' technical conditions based on the input data contained in vibroacoustic signal. Vibroacoustic signal is the main physical carrier of information about condition of elements of operating equipment during vibration diagnostics such signal being a collective concept that contains information on oscillating processes (vibratioal, hydro- or gas-dynamic etc.) and respective mechanism's acoustic noise in the environment.

The vast majority of the existing computerized diagnostic and forecasting systems, such as VIMOS (Swedish department of ABB) and ZOOM (VibroSystM Inc., Canada) and others are based on vibration signal analysis [1, 2]. With real-world vibroacoustic signals being of purely no stationary nature, the authors proposed to carry out spectral analysis using discrete wavelet transformation (DWT) resulting in acquisition of three-dimensional amplitude-frequency-temporal spectrum (AFTS).

It should be noted that, due to an exceptional complexity of the hydropower unit as a dynamic hydroelectromechanical system and practical impossibility of mathematical description of dependence between the vibroacoustic signal and all factors that cause vibration, it makes sense to treat the hydropower unit as the «black box», that is to simulate its external functioning rather than its structure.

Therefore, for the purposes of forecasting of fault development in hydropower units, the authors proposed the generation of artificial neural-like network (ANLN).This ANLN has successfully undergone field tests, as of today being a component part of the system for computerized diagnostics and forecasting of fault development in hydropower units (SCDF-DDH), which is stage-by-stage commissioned at DnestrHPP-2 [3, 4].

Artificial neural-like network for forecasting of fault development in hydropower units: structure, mathematical model, algorithm

Basic principles of ANLN generation for forecasting of fault development in hydropower units

For the purposes of ANLN generation, one should first determine, which information may arrive at ANLNentry and what we desire to obtain as a result of its functioning.

Measuring channels that ensure obtaining of vibroacoustic signals (vibratory acceleration) from vibration sensors (acceleration meters) represent a component part of SCDF-DDH.

As a rule, vibration sensors are situated in vertical and horizontal radial direction sat bearings, stator housing and other key assemblies of hydropower units.

For example, at horizontal hydropower units of DnestrHPP-2, vibration sensors are installed thrust-and-radial and turbine bearings. At hydropower units of Dnestr PSP, vibration sensors are installed at the generator and turbine bearings, turbine cover and face parts of stator winding.

In addition to vibroacoustic signals, SCDF-DDH obtains data related to hydropower unit's load power and rotation frequency, as well as to water level in water reservoir (for PSP–water levels in the lower water reservoir and upper accumulating pool).

These data are admitted by the routine monitoring system of SCDF-DDH, from where, following their initial processing, they are transferred to forecasting subsystems.

Each of the vibroacoustic signals obtained using DWT is decomposed in AFTS [5, 6].

Hence, the following data should arrive at ANLN entry:

Arrays of AFTS vibration signals are obtained by monitoring subsystem from vibration measuring channels (the number of arrays equals to the number of vibration sensors). For adequate functioning of forecasting subsystem, duration of each array should be quite long.

The value array of hydrogenerator load for each time moment of the same duration.

The value array of water head for each time moment of the same duration.

SCDF-DDH forecasting unit should come into action whenever there is a stable growth in absolute maximum values of wavelet coefficients in at least one frequency band of AFTS.

General structure of ANLNSCDF-DDH for forecasting of fault development in hydropower units

ANLN structure (as exemplified by Dnestr PSP) is shown in Figure1.

It should be noted that process units of pumped storage plants are return-type, that is capable of working in two (pump and turbine) modes. In the first mode, when consuming excessive power from the power system in minimum load hours, PSP pumps water from the lower water reservoir to the upper accumulating pool. In the second mode, PSP operates in maximum power consumption hours. By using water from the upper pool, it releases electric power to the system.

Apart from these modes, the so-called synchronous compensator mode, when only reactive power arrives to the system from return-type unit, can also be possible (quite infrequently).

It should be expressly indicated that voltage currents are different in all three modes. Besides, water levels in the lower water reservoir and in the upper accumulating pool differ from each other in the first two modes.

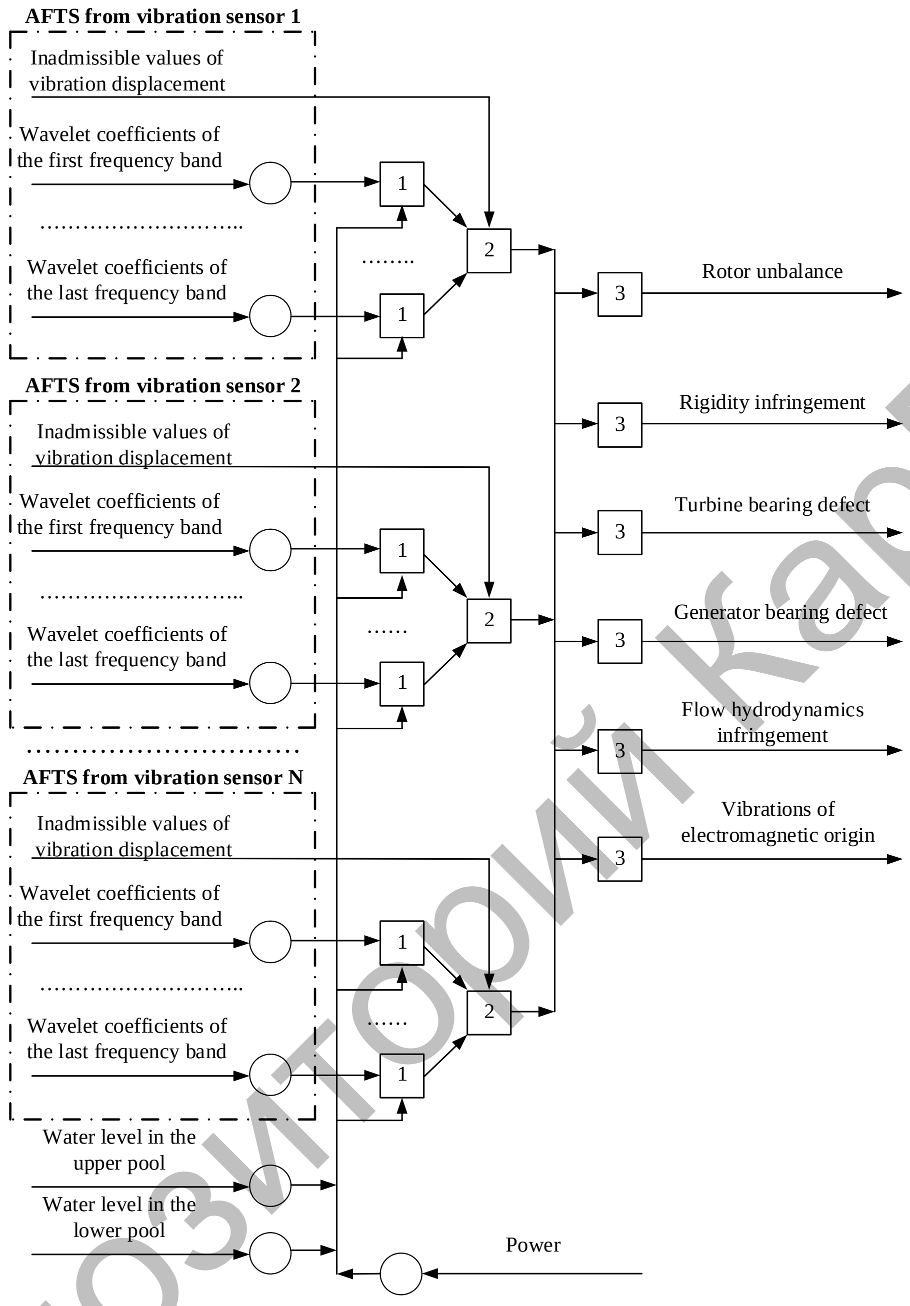

Figure 1. ANLN structure for forecasting of fault development in hydropower units

As compared to common hydropower units, vibration components have certain peculiarities [7].

For example, return-type hydropower unit shave two shafts, which strengthen the vibration component related to rotor unbalance.

Vibration components of electromagnetic origin also have their considerable distinctions. Since they are directly proportional to the unit's electric load, electrodynamic components will vary depending on each particular operating mode.

Hydrodynamic components also depend on the process unit's operating mode. In the pump mode, water flow is more laminar than in turbine one, that is why hydrodynamic vibration components are also lower in the pump mode than in turbine one. It is evident that, in the mode of synchronous compensator, hydrodynamic vibration components are absent at all.

As is seen from Figure1, provision is made for generation of three-layer no uniform non-standard ANLN.

The number of incoming neurons (in Figure 1 these are depicted as circles) depends on the number of frequency bands in AFTS of each of *N* vibration signals. Where the number of frequency bands in AFTS equals to M, the number of incoming neurons equals to $NM + 3$. Incoming neurons perform the function of acceptance of numerical data and sorting thereof.

Sizes of the numeric arrays that arrive at each incoming neuron are different. For example, the first incoming accepts one wavelet coefficient of the first frequency band, the second one — k wavelet coefficients of the second frequency band (k — DWT contraction coefficient), the third one — k^2 wavelet coefficients of the third frequency band, with each group's last neuron accepting k^{M-1} wavelet coefficients of the M^{th} frequency band.

The number of water level values in the lower water reservoir and in the upper accumulating pool with their temporal recordings may also fluctuate over a wide range, since the new level value should only arrive at the incoming neuron in case of its alteration. According to a similar principle, the data relating to hydrogenerator's load power also arrive.

The first ANLN layer (designated with digit 1) contains NM neurons. Each of them obtains wavelet coefficients of particular frequency band from respective in coming neuron and at the same time — value arrays of water heads and value array of hydrogenerator's load power.

First-layer neurons are meant for extraction of spectral components from the AFTS of each of N vibration signals caused by hydrodynamic and electrodynamic factors. And besides, these neurons should determine background spectral components for each frequency band of AFTS [8].

We are going to define vibration signal's spectral components as background ones, where the hydropower unit under diagnostics has stopped for some reasons, while other process units of Dnestr PSP are operating. Such being the case, vibration signals are generated by operating hydropower unit, being transferred via building structures to the shut-down hydropower unit, where they are recorded by its vibration sensors. Let us note that background spectral components should be determined separately for various operating modes — pump, turbine and synchronous compensator modes.

The second ANLN layer (designated with digit 2) contains N neurons. Each of them obtains the AFTS of one of N vibroacoustic signals, as well as inadmissible values of vibration displacements and their temporal recordings for this particular vibration signal. Besides, obtained in respect of each neuron are the data on possible dependence between particular frequency bands of respective AFTS and hydrodynamic and electrodynamic factors, as well as background spectral characteristics resulting from setting of the first ANLN layer.

Each neuron of the second layer determines the trends of wavelet coefficients of each AFTS frequency band of each vibration signal within particular time periods. Analysis of each trend is subsequently carried out in order to identify a stable growth of absolute maximum values of wavelet coefficients.

The third ANLN layer (designated with digit 3) contains 6 neurons, each of which corresponding to one of the factors causing vibrations.

Each third-layer neuron obtains all trends of wavelet coefficients of each AFTS frequency band of each vibration signal, as well as the data in possible dependence between particular frequency bands of respective AFTS, and hydrodynamic and electrodynamic factors, as well as background spectral characteristics.

Each third-layer neuron determines the probability that the reason for stable growth of particular vibration signal's trend lies in characteristic vibration factor that corresponds to this neuron. It is evident that this ANLN will only come into action in the event that at least one vibration signal comprises a stable growth of trends.

We should mention the possibility of situations, when several different characteristic vibration factors obtain high probability levels. Such being the case, ANLN will issue the diagnosis of the necessity in check during routine or extraordinary technical inspection of several hydropower unit's faults at the same time.

Mathematical model and algorithm of ANLNSCDF-DDH for forecasting of fault development in hydropower units.

First of all, let us note that all procedures set forth in this section shall be carried out with absolute values of wavelet coefficients.

As it was discussed in the previous sub-section, first-layer neurons should perform the following three functions:

– determine the background values of wavelet coefficients for each frequency band of idle hydropower unit under diagnostics;
– determine the dependence between wavelet coefficients of each frequency band and hydropower unit's load power;
– determine the dependence between wavelet coefficients of each frequency band and water head.

It is common knowledge that turbulence level is inversely proportional to the water head, i.e. this dependence is of a hyperbolical nature.

But as regards the dependence between vibration level and load powers, it is of a directly proportional nature, and to the first approximation it can be considered linear.

Of course, in the process of pilot operation of SCDF-DDH, the nature of these dependencies may be defined more specifically, but one can record as follows for diagnostic purposes:

For pump and turbine modes

$$\left|d_j\right| = D_{0xyj} + d_j^* + v_j P + \frac{1}{p_j + q_j\left(H_1 - H_2\right)^2}, \quad (1)$$

for synchronous compensator mode

$$\left|d_j\right| = D_{0xej} + d_j^* + v_j Q, \quad (2)$$

where $\left|d_j\right|$ — module of the wavelet coefficient of the jth frequency band at a particular moment of time; d_j^* — value of the wavelet coefficient of the j^{th} frequency band at a particular moment of time caused by the hydropower unit's own mechanical faults; H_1 — water level in the upper accumulating pool; H_2 — water level in the lower water reservoir; P — hydrogenerator's active load power (for pump or turbine mode); Q — hydrogenerator's reactive load power (for synchronous compensator mode); D_{0xyj} — background value of wavelet coefficient of the j^{th} frequency band at a particular moment of time (x — the No. of idle hydropower unit; y — the No. of operating hydropower unit); v_j — generalized numerical coefficient characterizing the dependence between the wavelet coefficients of the j^{th} frequency band and load power; p_j, q_j — generalized numerical coefficients characterizing the dependence between the wavelet coefficients of the j^{th} frequency band and the difference between water levels in the upper accumulating pool and lower water reservoir.

Let us note that, for instance, under conditions of Dnestr PSP the background value of wavelet coefficient D_{0xyj} for a shut-down hydropower unit at various moments of time may have different values, since different numbers of PSP hydropower units may operate simultaneously at a particular moment of time, with their vibration signals' amplitude being dependent on time-variant influencing values. Therefore one should determine the vector of background values, as

$$D_{03yj} = \left\{D_{031j}, D_{032j}, D_{0312j}\right\}. \quad (3)$$

p_j, q_j coefficients are only determined for those frequency bands, the wavelet coefficients of which grow with the decline of the difference between water levels in the upper accumulating pool and lower water reservoir (otherwise p_j, q_j are zeroed). In a similar way, coefficient v_j is only determined for those frequency bands, the wavelet coefficients of which grow with load power increase (otherwise v_j is zeroed). For those frequency bands, the wavelet coefficients of which react neither to water levels not to the load, only D_{0xyj} will be extracted from AFTS.

Hence, each first-layer neuron passes further to the ANLN, apart from the array of wavelet coefficients of the j^{th} frequency band, H_1, H_2, P (or Q), D_{0xyj}, v_j, p_j, q_j parameters as well.

As noted above, the purpose of the second-layer neurons lies in generation of wavelet coefficients' trends in each AFTS frequency band of each vibration signal during particular time periods. Each T_{ij} trend is a numeric set that may be recorded as follows

$$\forall i = 1, N \forall j = 1, M \forall r = 1, R\left(T_{ij} = \left\{\left|d_{ij1}^{\max}\right|, \left|d_{ij2}^{\max}\right|, \ldots, \left|d_{ijr}^{\max}\right|, \ldots \left|d_{ijR}^{\max}\right|\right\}\right), \quad (4)$$

where N — the number of vibration sensors; R — the number of incoming data stacks sized as 32768 values obtained from vibration sensors within a given time period; $\left|d_{ijr}\right|$ — maximum absolute value of wavelet coefficient of the j^{th} AFTS frequency band of the i^{th} vibration signal, which corresponds to the r^{th} stack of incoming data.

Further on, one shall carry out analysis of each trend with the aim to identify a stable growth of absolute maximum values of wavelet coefficients.

The evaluation criterion for such growth during pilot operation of SCDF-DDH may be defined more specifically, but it is a priori adopted as follows:

$$\frac{\sum_{r=1}^{N}\left|d_{ijr}^{\max}\right|}{R}-\frac{\sum_{r=1}^{\frac{N}{2}}\left|d_{ijr}^{\max}\right|}{\frac{R}{2}}>\varepsilon, \tag{5}$$

where ε — the parameter characterizing the degree of trend growth.

ε value should be defined more specifically during pilot operation of SCDF-DDH, but at first one can adopt is as equal to 10 % of the average value of the trend's wavelet coefficients, that is:

$$\varepsilon = 0.1\cdot\frac{\sum_{r=1}^{N}\left|d_{ijr}^{\max}\right|}{R}. \tag{6}$$

Upon completion of the analysis, all T_{ij} trends with a stable growth in wavelet coefficients (and only these ones), together with H_1, H_2, P, D_{0xyj}, v_j, p_j, q_j parameters, arrive at the third ANLN layer. Let us designated these trends as $T_{ij}^{\uparrow}$.

Each neuron of the third ANLN layer should adhere to the following procedures:

1. At first, one should define the Z array, which contains last elements of each growing trend

$$\forall\left|d_{ijR}^{\max}\right|\in T_{ij}^{\uparrow}\left(\left|d_{ijR}^{\max}\right|\in Z\right). \tag{7}$$

2. Further on, for each element of Z array, one should separate the background, the hydrodynamic and the electrodynamic spectral components from the components caused by other factors, and namely:

– for the first four neuron directly characterizing the hydropower unit's mechanical faults, this is made using the formula:

$$\forall k=1,4\forall\left|d_{ijR}^{\max}\right|\in Z\left(d_{kij}^{*}=\left|d_{ijR}^{\max}\right|-D_{0xyj}-v_jP-\frac{1}{p_j+q_j\left(H_1-H_2\right)^2}\right), \tag{8}$$

where $d_{kij}^{*}<0$, this value will be zeroed;

– for the fifth neuron, which should diagnose breaches in flow hydrodynamics, one can record as follows:

$$\forall\left|d_{ijR}^{\max}\right|\in Z\left(p_j\neq 0\wedge q_j\neq 0\Rightarrow d_{5ij}^{*}=\frac{1}{p_j+q_j\left(H_1-H_2\right)^2}\right); \tag{9}$$

– for the sixth neuron, which should diagnose the electrodynamic vibration component, one can record as follows:

$$\forall\left|d_{ijR}^{\max}\right|\in Z\left(v_j\neq 0\Rightarrow d_{6ij}^{*}=v_jP\right). \tag{10}$$

3. The next step lies in standardization of all d_{kij}^{*} elements, which is performed using the formula:

$$\forall k=1,6\forall\left|d_{ijR}^{\max}\right|\in Z\left(d_{kij}^{norm}=\frac{d_{kij}^{*}}{\sum_{k,i,j}d_{kij}^{*}}\right). \tag{11}$$

4. The probability value of PV_k factor, which corresponds to the k^{th} neuron, shall be defined as follows:

$$\forall k=1,6\forall\left|d_{ijN}^{\max}\right|\in Z\forall j\in\Psi_k\left(\Rightarrow PV_k \quad \sum_{i,j}w_{kij}d_{kij}^{norm}\right), \tag{12}$$

where w_{kij} mean the weight coefficients that define the significance of taking into account the wavelet coefficients of the j^{th} AFTS frequency band of the i^{th} vibration signal at the probability level of the k^{th} neuron.

Correlation approach [9, 10] is proposed for determination of weight coefficients.

The relative probability level of the k^{th} neuron is defined as follows:

$$RV_k = \frac{PV_k}{\max\left(PV_1, PV_2, PV_3, PV_4, PV_5, PV_6\right)}. \tag{13}$$

Hence, the resulting diagnostic conclusion may be formulated as the value array of probability levels for various vibration factors $\{RV_1, RV_2, RV_3, RV_4, RV_5, RV_6\}$.

Figure 2 shows the control flow chart corresponding to the above mathematical model.

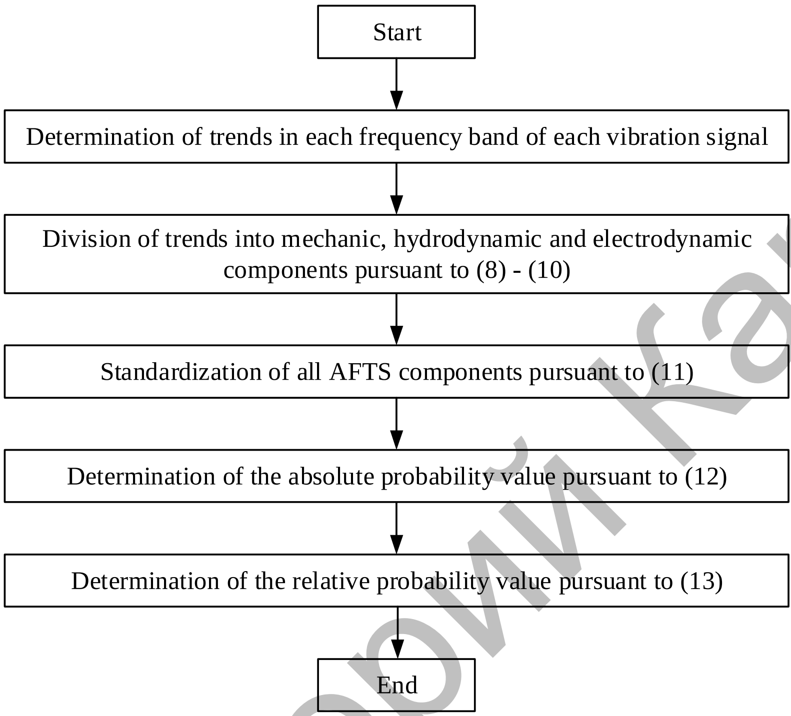

Figure 2. ANLN control flow chart for forecasting of hydropower units' fault development

The following sub-section is dedicated to examples of diagnostic conclusions obtained for hydrogenerators of Dnestr HPP-2 [11].

Preliminary estimated conclusions relating to hydropower units' fault development at DNESTR HPP-

Let us consider a number of examples obtained through the application implemented using the algorithm shown in Figure 2.

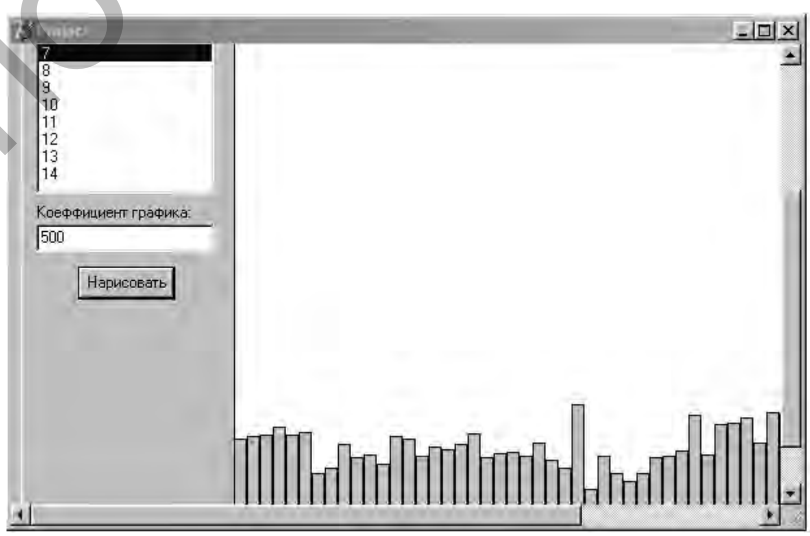

Figure 3. The trend of the 7th frequency band of AFTS vibration signal

Figure 3 depicts a trend of the 7th AFTS frequency band of the vibration signal, such trend having been obtained from the vibration sensor installed at the turbine bearing. Even without using criterion (5), one can see that this trend is practically unchangeable, and there is no need to transfer the same to the neurons of the third ANLN layer.

The trend depicted in Figure 4 is more interesting.

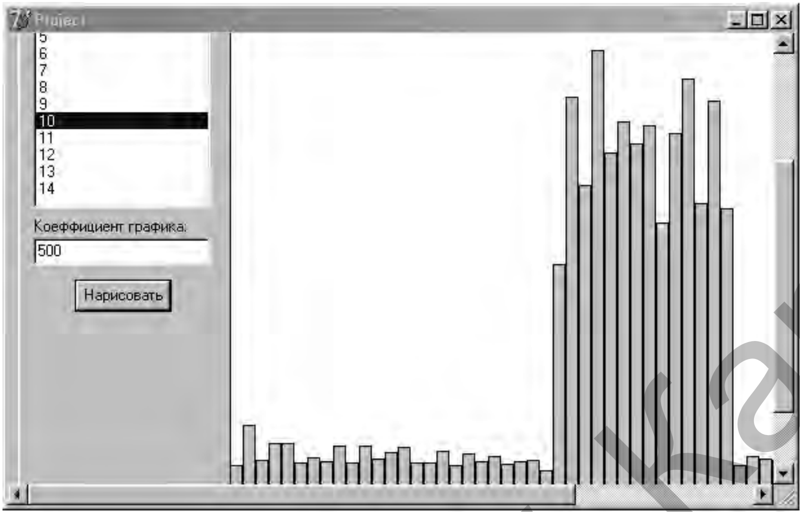

Figure 4. The trend of the 10th frequency band of AFTS vibration signal

In this case, it would be advisable to pass this trend to the third neuron layer and to investigate the reasons for its growth, since this growth may likely be caused by a temporary drop in the water head.

When analyzing the data of monitoring sub-system, one can obtain particular preliminary results. A fragment of interface of the application that implements the algorithm (see Fig. 2) is shown in Figure 5.

Digits 1 to 4 designate the neuron blocks processing the vibration signals from the vibration sensors installed at the turbine and thrust-and-radial bearings along the horizontal and vertical axes.

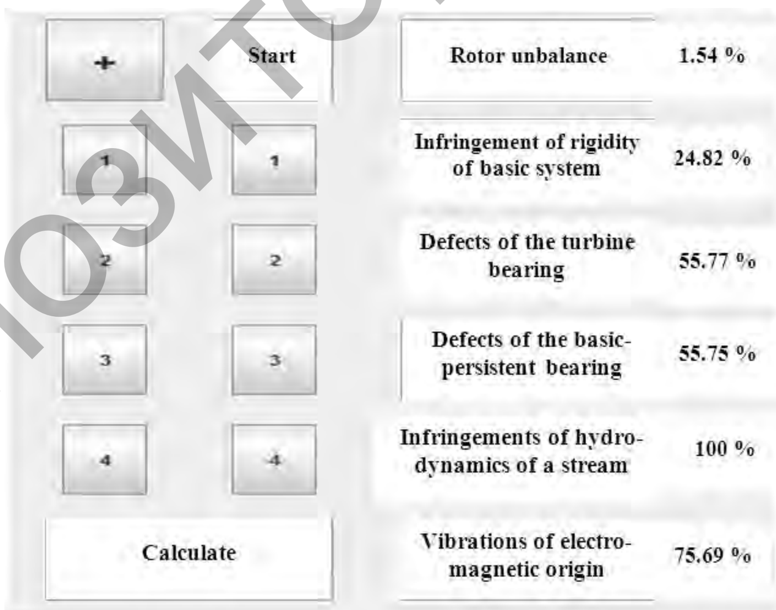

Figure 5. Results of historical data processing by the application

It follows from Figure 5 that the highest probability level (100 %) is associated with a stable trend growth caused by hydrodynamic factors, while a high probability (75.69 %) is associated with the growth caused by vibrations of electromagnetic origin etc.

Conclusions

1. With real-world vibroacoustic signals being of purely no stationary nature, the authors proposed to carry out spectral analysis using discrete wavelet transformation resulting in acquisition of three-dimensional amplitude-frequency-temporal spectrum.

2. Due to an exceptional complexity of the hydropower unit as a dynamic hydroelectromechanical system and complexity of mathematical description of dependence between the vibroacoustic signal and all factors that cause vibration, it makes sense to treat the hydropower unit as the «black box», therefore, for the purposes of forecasting of fault development in hydropower units, generation of three-layer artificial neural-like network is proposed by the authors.

3. Since vibration is caused by a simultaneous action of all factors without any exception, forecasting of development of faults in hydropower units lies in the extraction of significant influencing factors, which is proposed to be done by way of ANLN study and introduction of respective weight coefficients.

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Гидроагрегаттарда ақаулардың дамуын дірілді-болжау

Мақалада дірілді дабылдардың спектрлік талдауларына негізделген гидроагрегаттарда ақаулардың дамуын дірілді-болжаудың математикалық модельдері және алгоритмдері ұсынылды. Дірілді акустикалық дабылдар стационарлы емес сипатта болатындықтан, яғни олардың спекторлары уақыт бойынша өзгеретіндіктен, авторлармен спектралды талдауларды дискретті вейвлет-түрлендіргіш көмегімен іске асыру ұсынылған. Нәтижесінде вейвлет-коэффициенттер матрицасы түріндегі үшөлшемді амплитуда-жиілікті-уақыттық спектр алынады. Гидроагрегаттың динамикалық гидро-электрмеханикалық жүйе ретінде ерекше күрделілігіне және виброакустикалық дабылдың дірілдің барлық себептеріне тәуелділігінің математикалық сипаттамасының практикалық мүмкін болмауына байланысты, гидротехникалық құрылғыны «қара жәшік» ретінде қарастыруға негіз бар, яғни оның құрылымын емес, сыртқы жұмыс істеуін модельдеу керек. Сондықтан гидроагрегаттағы ақаулардың дамуын болжау үшін үшқабатты жасанды нейрондық желіні салу жоспарлануда. Болжау діріл-акустикалық дабылдың амплитуда-жиіліктік-уақыт спектрі жиілігінің әрбір қабатының тренд вейвлет-коэффициенттерін талдауға негізделген. Сонымен қатар трендтерді діріл тудыратын белгілі бір

факторларға сәйкес дірілді дабылдарды құраушыларға (фонды, гидродинамикалық, электродинамикалық және т.б.) бөлу арқылы қарастырылды. Бұл компоненттерді өңдеу әртүрлі діріл факторларының сенімділік деңгейлерінің жиынтығы ретінде гидроагрегатта ақаулардың дамуына қатысты болжам қорытындысын анықтауға мүмкіндік берді. Сондай-ақ Днестр ГЭС-2 діріл бақылау жүйесінен алынған діріл-акустикалық дабылдардың мұрағатталған мәндері негізінде алынған болжамды тұжырымның мысалы келтірілген.

Кілт сөздер: дірілді акустикалық дабыл, дискретті толқындардың түрленуі, толқындық коэффициенттер, жасанды баламалы желі, жиілік диапазоны, ықтималдық мәні.

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Вибро-прогнозирование развития нарушений в гидроагрегатах

В статье предложены математические модели и алгоритмы прогнозирования развития дефектов гидроагрегатов, которые основаны на спектральном анализе вибросигналов. Так как реальные виброакустические сигналы имеют существенно нестационарный характер, т.е. их спектры изменяются во времени, авторами предложено осуществлять спектральный анализ при помощи дискретного вейвлет-преобразования, в результате которого получается трехмерный амплитудно-частотно-временной спектр в виде матрицы вейвлет-коэффициентов. Отметим, что из-за исключительной сложности гидроагрегата как динамической гидроэлектромеханической системы и практической невозможности математического описания зависимости виброакустического сигнала от всех причин, вызывающих вибрацию, имеет смысл рассматривать гидроагрегат как «черный ящик», т.е. моделировать не его структуру, а внешнее функционирование. Поэтому для прогнозирования развития дефектов гидроагрегата предусматривается построение трехслойной искусственной нейроподобной сети. Прогнозирование основано на анализе трендов вейвлет-коэффициентов каждой полосы частот амплитудно-частотно-временного спектра виброакустического сигнала. Далее предусматривается разделение этих трендов на составляющие вибросигналов (фоновую, гидродинамическую, электродинамическую и т.д.), которые соответствуют определенным факторам, вызывающим вибрацию. Обработка этих составляющих позволяет определить результирующий прогнозный вывод относительно развития дефектов гидроагрегата как множество значений уровней достоверности разных факторов вибрации. В работе также приведен пример такого прогнозного вывода, полученного на основании архивных значений виброакустических сигналов, которые поступили от подсистемы вибромониторинга Днестровской ГЭС-2.

Ключевые слова: виброакустический сигнал, дискретное вейвлет-преобразование, вейвлет-коэффициенты, искусственно-эквивалентная сеть, полоса частот, значение вероятности.