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ON PECULIARITIES OF DEVELOPMENT OF INFORMATIONAL SUPPORT FOR TECHNICAL DIAGNOSTICS MULTILEVEL SYSTEMS OF ELECTRICAL EQUIPMENT

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Abstract: Crucial requirements to the diagnostics systems of electrical equipment have been formulated which take into account the conception of Smart Grid. Results pertaining to the issues of diagnostic signals formation in operating electrical equipment are considered. Informational support for multilevel systems of electrical equipment has been presented. The basic components of the informational support are discussed, including mathematical models of diagnostic signals, and also models simulating the process of forming the training datasets; the latter cover both certain defects of investigated electrical equipment units and their operating modes. Various representations of training datasets have been introduced and investigated; the datasets cover certain technical conditions of electrical equipment units in the variety of operating modes.

Key words: electrical equipment, diagnostics system, conception of Smart Grid, training dataset.

1. Key tasks of electricity supply industry in Ukraine

According to different estimations [1, 2], currently from 70 to 90 % of core equipment and 80 % of internal consumption equipment in Ukraine have already served out. For further reliable operation of this equipment, it is necessary either fully to replace it, or to equip it with modern monitoring facilities, which, with high probability, would determine the residual capacities and thus provide overall increase in its operating reliability. The first way of resolving the problem, i. e. replacement, requires enormous expenses (about 50 milliards US dollars). The second way envisages recurring determination of the actual technical condition and the residual capacities of operating electrical equipment (EE); that way encompasses development and application of modern methods and monitoring/diagnostic facilities.

Reliability performance measures of power equipment are determined by influence of operating conditions and internal factors characterizing the features of the power equipment. The combination of such factors is of random character. Therefore, as a matter of practice, for resolving such tasks expediency dictates the application of statistical methods.

The most effective methods of monitoring and testing are so-called non-destructive methods [3-6], which usually are implemented by means of task-oriented computer systems.

A couple of sources [7–12] underscores that modern power engineering, taking into account the transition to application of intellectual networks built on the basis of Smart Grid conception, requires to develop an integral multilevel control system providing the high level of automation and reliability of the overall system, embraces power producers, transmission and distribution networks, consumers, etc. The availability of actual information on the actual condition of every power unit and the exchange of the information among all participants of electric power market, which increases the reliability of the overall system, is of great importance.

As a result, one of key tasks in modern power engineering is development of methods and technical devices for monitoring of the conditions of separate electrical units and their testing [7, 9, 10], which would carry out real-time deep testing of the condition of separate electrical units, provide processing of such diagnostic information, select from the large data array the information that is critical for the overall system, and transmit it to the higher hierarchy level.

As it was highlighted in many works [8, 9, 10], a multilevel system for EE diagnostics, embodying the conception of Smart Grid, is structured according to such principles:

- decentralization of computational resources with the aim of ensuring the necessary frequency of measurements and processing of diagnostic signals received by specified devices;
- structuring of diagnostic information on hierarchical principle;
- classification of diagnostic information in accordance with its critical importance, for optimization of data flow between the hierarchical levels of the system.

Implementation of such system gives an opportunity to ensure the exact and timely exposure of defects of the most loaded units of power equipment (PE) by means of permanent deep diagnostics of their condition; timely informing the maintenance personnel of the place and type of defect and transmission of processed information transfer on the actual condition of the unit in question the higher hierarchy level for prompt response [8, 9, 10]. In the end, it would improve the reliability of the overall power system and ensure high quality of electricity, which is an important prerequisite for the integration of the Ukrainian grid into the unified European system (UES).

As it results from analysis of different sources [13, 14], in the process of development of a multilevel diagnostics system, it is crucial to take into account a variety of operating modes of EE units to ensure the receipt of reliable information on their technical condition.

Taking into account the above considerations, the primary **purpose of this article** is development of informational support for the multilevel diagnostics system of electrical equipment that provides functioning of a system implementing the conception of Smart Grid.

In the process of solving the task of EE technical condition testing, physical processes responsible for operation of the equipment are the primary source of information. In other words, those physical processes are informational diagnostic signals; their parameters and features describe the technical condition of specified EE units. It should noticed that an operating EE comprises both moving and stationary components, which influences both the measurement methods diagnostic signals and their processing methods (filtration, taking into account of cyclical nature dictated by the frequency of rotating electromagnetic field, etc). It must be taken into consideration when a mathematical model for the description of the physical processes in EE units is selected. Those issues are discussed in details in [3, 6, 7, 14–17].

2. Matematical models of diagnostic signals

As the mentioned sources show, such processes as vibrations, electromagnetic processes, acoustic emissions, thermal processes, etc are the most informative processes characterizing the technical condition of EE units. In our following research, vibration processes – as main carriers of diagnostic information – are used for the description of application peculiarities of a multilevel diagnostics system of EE units.

Rotating electric machines (EM) are most typical units of an operating EE comprising both moving and stationary components. A lot of publications is concerned with the problem of vibrations in various EM elements; the most significant of them are [3, 7, 15–21]. As it was shown in these works, EM vibrations are triggered by the impact of electromagnetic forces; forces attributed to work of rolling bearings and commutator; aerodynamic forces; forces caused by the mechanical disbalance of rotors.

Among the enumerated triggers of EM vibrations, the vibrations of rolling bearings are most significant [3, 7, 17, 18, 19]. The vibrations of active rolling bearings are caused by four basic factors: resonances of bearing elements and its retention; functioning of bearing elements; acoustic radiation; external vibrations.

It should be noted that external vibration of bearings is caused by connection between rotating and stationary parts of EM. Thus, a bearing unit is the basic place for transmission of vibrations from moving units to stationary ones.

To develop the structure of the multilevel information-measuring diagnostic system (IMDS) and to choose necessary software and hardware solution, the mathematical models of EE units' vibrations are considered. The methodology of developing the IMDS structure remains identical for any EE and does not depend on the type of carrier of diagnostic information.

Mathematical models forming a part of IMDS informational support can be divided into two basic groups:

– Models of diagnostic signals analyzed to obtain indices used for testing of EE units technical condition;

– Models of forming the training datasets that characterize the EE units condition.

The mathematical models of diagnostic signals – that characterize the technical condition of EE units – provide theoretical substantiation of diagnostic signals determining the technical condition of investigated units. Namely those diagnostic signals determine the choice of algorithms and software for multilevel IMDS.

In general case, a simplified mathematical model describing processes, going on at a functioning object to be diagnosed, and taking into account their operating modes is presented as follows

$$\Xi = \psi\left[\mathbf{H}, \mathbf{\Phi}(t,\theta), t\right], \tag{1}$$

where Ξ is j-dimensional vector; its elements are j input functions $\xi_1(t), \xi_2(t), \ldots, \xi_j(t)$; $\mathbf{H}$ is n-imensional vector; its elements of that are n input functions $\eta_1(t), \eta_2(t), \ldots, \eta_n(t)$; $\mathbf{\Phi}(t,\theta)$ is m-dimensional vector; its elements are m internal functions $\varphi_1(t,\theta), \varphi_2(t,\theta), \ldots, \varphi_n(t,\theta)$ of the object to be diagnosed; t is time; $\psi[\bullet]$ is, in a general case, a nonlinear functional mapping from vector spaces indicated above; it is time-dependable. In the presented relation (1), the parameter θ characterizes the operating mode of the investigated object. This parameter θ can characterize speed, temperature, load conditions and other EE working modes.

In the similar way, the mathematical model – that takes into account any other operating modes – of a functioning object to be diagnosed can be represented.

As it was shown [3, 7], the model of wide range of diagnostic processes can be represented by linear stochastic processes (LSP). It is important that general form of characteristic function for LSP models is well-known. It facilitates the determination of both the moments of the process of any order (providing they exist) and finite-dimensional distributions of the process [3, 7, 14, 22].

As the conducted theoretical research and experiments [3, 7, 14, 15] showed, the vibrations of a wide class of engineering objects, and in particular of many EE units, have a distinct multi-resonant structure. Therefore, a mathematical model describing the multi-resonant vibration processes is chosen; it also provides for further consideration of EE operating modes.

The mathematical model of vibrations in EE units can be developed on the basis of LSP [3, 7, 22]. It is done under the assumption that the investigated unit – as a mechanical system – has linear characteristics, i. e. its response is always proportional to excitation. As a result:

– frequency characteristics of the investigated mechanical system do not depend on the level of excitation (property of homogeneity);

– frequency characteristics of the investigated mechanical system do not depend on the type and shape of excitation wave (property of superposition).

Additionally:

– there is some causality is certain, i. e. the mechanical vibrations of units do not appear by, and they are a result of some influence;

– vibrations demonstrate steadiness, i. e. they attenuate within some time after excitation is terminated;

– features of the investigated mechanical system do not change during an experiment (time-invariance).

The proposed assumptions allow us to mathematically describe an investigated unit as some linear time-invariant system.

The EM vibrations have a stochastic character [3, 7, 14, 17]; therefore, for their mathematical representation, that or another class of random processes can be used. To accomplish the probabilistic analysis of a random process $\xi(t)$, it is necessary to describe it in some way. Probability theory offers to use for this purpose a sequence of finite-dimensional distribution functions.

Obviously, this way of description is very cumbersome. The method of stochastic integral representations was proposed [3, 14, 22], which gives an optimal way for description of a sufficiently wide class of random processes. According to those works, a process occurring as the response of a linear system to white-noise excitation, can be described by LSP mathematical model; in that case, white noise is represented by the generalized derivative of some infinitely divisible random process.

The features of Hilbert's linear processes, i. e. processes with finite dispersion and characteristic function presentable in the Kolmogorov canonical form, as well as feasibility of their utilization for classification of information signals in different applications were investigated [3, 22]. As a result, the methods of full probabilistic LSP analysis were developed; in particular, formulae for determination of characteristic functions (ChF) and moments of a process of any order by the parameters of an input (generating) process and the characteristics of the linear system (its kernel) were elaborated. Thus, the LSP theory has become a comfortable mathematical vehicle for the analysis of linear systems responses described by a LSP model.

Therefore, the response of an investigated EE unit to some impulse excitation is described by a LSP model.

A linear stochastic process can be represented by stochastic integral of such a form

$$\xi(t) = \int_{-\infty}^{\infty} \phi(\tau,t)\, d\eta(\tau),\ t \in \mathbf{T},\ \mathbf{T} \subset \mathbf{R}, \qquad (2)$$

where $\varphi(\tau,t)$, $\tau \in (-\infty,\infty)$, $t \in \mathbf{T}$ is a real non-random numerical function (kernel (2)), such that $\int_{-\infty}^{\infty} |\varphi(\tau,t)|^p d\tau < \infty$ is uniformly continuous in t at $p = 1, 2$; $\{\eta(\tau),\ \mathbf{P}\{\eta(0)=0\}=1, \tau \in (-\infty,\infty)\}$ is stochastically continuous random process with independent increments.

The non-probabilistic function $\varphi(\tau,t)$ is called the kernel of integral transform (2). The generalized derivative of $\eta(\tau)$-process – that is $\zeta(\tau) = d\eta(\tau)/d\tau$ (generating process) – is a white-noise-type random process because of independence of $\eta(\tau)$-process increments [3, 22]. Thus, LSP can be understood as the response of a linear system, described by an impulse response function $\varphi(\tau,t)$, to white-noise (i. e. $\eta'(\tau)$) excitation.

If $\eta(\tau)$-process is a process with uncorrelated increments, the formula (2) describes a linear stochastic process. Taking into account the fact that diagnostic signals are formed by a real physical system, $\xi(t)$-process must have finite values of power characteristics. Thus we suppose $\xi(t)$-process to be a

Hilbert's process, i. e. $\mathsf{M}\left[|\xi(t)|^2\right] < \infty$ and dispersion of $\eta(\tau)$-process increments is finite [22]. If the function $\phi^k(\tau,t)$, $k=1, 2, \ldots$ is integrable on τ at all t and all cumulants up to k-th order of $\eta(\tau)$-process exist at $\tau=1$, then mixed cumulants for the values of $\xi(t)$-process of k-th order at t_1, ..., t_k also exist. As it was previously shown [3, 22], they are determined by the following formula:

$$\kappa_k\left[\xi(t_1),\ \ldots,\ \xi(t_k)\right] = \kappa_k \int_{-\infty}^{\infty} \prod_{j=1}^{k} \phi(\tau,t_j)d\tau, \quad k=1,\ 2,\ \ldots, \tag{3}$$

where κ_k is k-th cumulant of random variable $\eta(1)$.

In particular, the expressions for mean (expected value) $\mathsf{M}[\xi(t)]$ and correlation function $R_\xi(t_1,t_2)$ of LCP (2) are as follows:

$$\mathsf{M}[\xi(t)] = \kappa_1 \int_{-\infty}^{\infty} \phi(\tau,t)d\tau, \quad R_\xi(t_1,t_2) = \kappa_2 \int_{-\infty}^{\infty} \phi(\tau,t_1)\phi(\tau,t_2)d\tau. \tag{4}$$

The latter expressions are used for the theoretical justification of diagnostic indices selected for evaluation of the technical conditions of EE units by their vibration responses to impulse excitation.

The main advantage of LSP model is the fact that basic probabilistic characteristics of the process (2), such as distribution moments, correlation function, characteristic function, can be represented by parameters of generating process $\eta(\tau)$ and kernel $\phi(\tau)$ of the process. Additionally, linear operations (integration, differentiation) on the processes described by the formula (2) produce as a result the processes of the same kind (2).

Since for a linear stochastic process $\xi(t)$ described by the formula (2) $\int_{-\infty}^{\infty} \phi^2(\tau,t)d\tau < \infty$, the logarithm of one-dimensional characteristic function is determined by the following expression [3, 22]:

$$\ln f_\xi(u) = = ium\sum_{j=1}^{n} a_{jn} + \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\left[\exp\left(iux\sum_{j=1}^{n} a_{jn}\phi_j(\tau)\right) - -1 - iux\sum_{j=1}^{n} a_{jn}\phi_j(\tau)\right]\frac{dK(x)}{x^2}d\tau, \tag{5}$$

where $\varphi_j(t)$, $j=\overline{1,n}$, is determined by the formula (2); m and $K(x)$ are parameters of the characteristic function of generating process $\eta(\tau)$ in the Kolmogorov form; a_j are some weight coefficients.

Applying the models (1) and (2) as well as basic provisions of LSP theory, the mathematical model of vibration process of an investigated object can be presented as LSP-vector as follows

$$\Xi_n(t) = \left\{\xi_1(1), \xi_2(t), \ldots, \xi_n(t)\right\}, \quad t\in T, \tag{6}$$

where the sequence of components $\{\xi_j(t),\ j=\overline{1,n}\}$ of the model (6) describes the sequence of diagnostic EE vibration signals in its n operating modes.

The model (6) is a LSP-vector which enables taking into account the specificity and characteristic variances of different operating modes of investigated EE. The offered model is further development of well-known mathematical models of diagnostic signals [3, 4, 17, 20, 21] obtained by examination of physical processes responsible for EE functioning. A model of stationary LSP being widely applied in vibration-based diagnostics of engineering objects and systems is analyzed in this article.

Thus, the component $\xi_j(t)$ of the model (6) is represented by a following integral:

$$\xi_j(t) = = \int_0^{\infty}\phi_j(t-\tau)d\eta(\tau) = \int\phi_j(t-\tau)\eta'(\tau)d\tau, \quad \overline{j=1,n},\ t\in T \tag{7}$$

where a non-probabilistic function $\varphi_j(t)$ characterizes the impulse response function of an investigated object – as a linear system – in its j-th operation mode; a generative process $\eta(t)$ is a random process with independent increments and infinitely-divisible distribution function; it takes into account the impact of variety of stochastic factors occurring when the diagnostic signal is formed. The derivative $\eta'(\tau)$ is a white-noise process providing for utilization of both theoretical and experimental research results obtained in the area of vibration-based diagnostics.

Investigated EE units are a multi-resonant oscillating system. As a result of linearity assumption pertaining to the investigated units, this system can be represented by linear combination of oscillating systems of the second order [3, 22]. Thus, a shock– wave of vibration in a measurement point is examine in the form of a weighted sum of random processes, each of those is a response of the corresponding oscillating system of the second order to the applied shock impact:

$$\xi_j(t)=\sum_{i=1}^{m} a_{ji}\,\xi_{ji}(t),\ j=\overline{1,n},\ t\in T. \quad (8)$$

where $m\in N$ is an integer characterizing the number of resonant frequencies; a_{ji} are weight coefficients representing the relations between corresponding resonant frequencies energies; the constituent $\xi_{ji}(t)$ takes into account the signal characteristics for frequencies close to *i*–th resonance and is defined by such a formula:

$$\xi_{ji}(t)=\int_0^{\infty}\phi_{ji}(t-\tau)\eta'(\tau)\,d\tau\,, \quad (9)$$

where $\phi_{ji}(t)$ is an impulse response function of *i*–th forming resonant filter.

Taking into account the time-invariance of the investigated system and also insignificant attenuation of a real physical system (i. e. $2\pi f>\beta$), the impulse response function of *i*–th forming resonant filter can be presented in such a form:

$$\phi_{ji}(t)=\frac{\left(2\pi f_{ji}\right)^2}{\psi_{ji}}e^{-\beta_{ji}t}\sin\left(\psi_{ji}t\right)U(t), \quad (10)$$

where f_{ji} is a resonant frequency; β_{ji} is a coefficient characterizing the attenuation degree of *i*–th oscillating constituent; $\psi_{ji}=\sqrt{\left(2\pi f_{ji}\right)^2-\beta_{ji}^2}$ is a coefficient characterizing the degree of correlation between f_{ji} and β_{ji}; $U(t)$ is normalized Heaviside function (unit step).

The change of EE operating mode results in the change of the internal characteristics of the investigated object $\phi_{ji}(t)$ (6), (7) as well as functional characteristics of measured diagnostic signals $\xi_j(t)$ (8), (9).

When a diagnostic signal does not change in the operating mode of an investigated EE unit, it is a case of stationary functioning of the unit. In such a case the type of basic functional characteristics – namely, correlation function $R(s)$, power spectrum density $S(f)$, and characteristic function $f(u,t)$ – of investigated vibrations remains unchanged for any EE operating modes. Such situation allows us to use basic expressions for the indicated functional descriptions obtained in works [3, 7] for a fixed EE operating mode.

On the basis of the proposed mathematical models of vibration-based diagnostic signals, the sequence of selected diagnostic indices is justified; the takes into account both various modes and possible technical condition of EO tested object, e.g. for correlation and spectral analysis: attenuation coefficients β_{ji}, frequency parameters ψ_{ji}, $j=\overline{1,n}$, $i=\overline{1,m}$; for probability distribution analysis: character of probability density function; values of raw and central moments, among which the most informing ones are asymmetry coefficient k and excess coefficient γ.

3. Models of forming the training datasets characterizing EE units conditions

One of key tasks of power engineering is development of methods and technical devices for monitoring and diagnostics of the conditions of power system units in real-time regime, generalization of such diagnostic information, selection from the large data array the information that is critical for the system as a whole, and its transmission to the higher hierarchy level [7, 8, 9].

The implementation of the formulated goal is possible by development of an intellectual distributed multilevel system for monitoring and diagnostics of PE condition.

In practice, when systems, based on previous training and oriented to application of Smart Grid technologies, are used, there arise issues related to principles of formation of training datasets and following organization of their utilization for determination of technical condition of certain EE or its unit. It should be noted that the monitoring and diagnostics systems built according to Smart Grid technology must work in real-time regime, i. e. such system must promptly find, in the bank of training datasets, an appropriate dataset containing information pertaining to both the defect type of the object and its operating mode.

When, in the course of formation of training datasets (so-called etalons), functional diagnostics is performed, there arises a task of choice of diagnostic spaces corresponding to various technical conditions of units and their modes, e. g. EM rotor speed, temperature of tested units, various degrees of the electrodynamic load, etc. As it was stated in [23], in modern mathematics, "... *space* is a logically conceivable form (or structure) that serves as an environment, where other forms and constructions actualize…" In our case, "*space* is understood as a *set of any objects* called its points; geometric figures, functions, physical system states, etc may be such points…" According to [3, 7, 14, 15], parameters or functional characteristics of diagnostic signals, which have proven to be most sensible to the change of the technical condition of investigated objects, are usually chosen as coordinates of diagnostic spaces. Diagnostic space dimension is directly related to the number of coordinates; diagnostic signals are measured by sensors.

If statistical diagnostic models are chosen, certain statistical parameters and characteristics, which have proven to be most helpful for detection and classification of different types of defects in EE units, are included into the diagnostic space Ω as a set of diagnostic indices.

As a result, parameters and characteristics of diagnostic signals can be obtained by considering them to be realizations of random processes or fields.

$$\xi(\omega) \rightarrow \begin{cases} \xi(\omega,t), \omega \in \Omega, t \in T \\ \xi(\omega,r,t), \omega \in \Omega, r(x,y,z), t \in T. \end{cases} \quad (11)$$

As diagnostic space Ω for formation of training datasets (TD), the ellipse of dispersion – well-known in statistics – is selected. Taking into account such apprehension of diagnostic signals measuring, it is possible to illustrate the forming of diagnostic space by a schematic diagram (Fig. 1). In upper part of Fig. 1, Ω is the space of the set of diagnostic indices determined by corresponding statistical parameters and characteristics. As numerous theoretical and experimental studies [3, 7, 14] showed, the most informative among such parameters are raw and central moments (cumulants) up to the j-th order, and most the informative among such characteristics are correlation function $R(\tau)$, power spectrum density $S(f)$, probability density function $p(x)$, and characteristic function $f(t,u)$.

It should be also mentioned that the formation of training datasets is accomplished for a tentatively selected tested object and its comprising units. Additionally, the list of possible defects is formed for each unit taking into account its type, structural features and purpose. It should also be noted that information capacity of specific diagnostic indices depends on the selected object (or its constituents) [3, 7, 14].

The lower part of Fig. 1 depicts a schematic diagram for illustration of the principle used for formation of subspaces of diagnostic indices sets $\omega_1, \omega_2, \dots, \omega_n$; they correspond to good condition of the object or to presence of certain types of defects (defect 1, defect 2, defect n) and are elements of the space Ω, i. e.

$$\omega_1, \omega_2, \dots, \omega_n \in \Omega. \quad (12)$$

Such a family of subspaces is built separately for each of tested objects. For our purpose, Fig. 2 shows those subspaces built for object 1, and this object may be any EE unit for which the diagnostics operations are performed, e. g. powerful EM, transformers, electric motors of internal consumption, etc.

Pursuant to [3, 7, 14, 15], the finishing stage of EE diagnostics comprises detection and classification of certain types of defects that can arise in investigated EE units. As the mentioned works indicated, performing of those operations envisages the presence of training datasets that correspond to certain types of defects in the tested EE units. In addition, to obtain reliable diagnostics results, it is necessary to take into account EE operating modes. It means that the formed training datasets must concurrently take into account both the possible types of defects and EE operating modes. ***R(τ)***

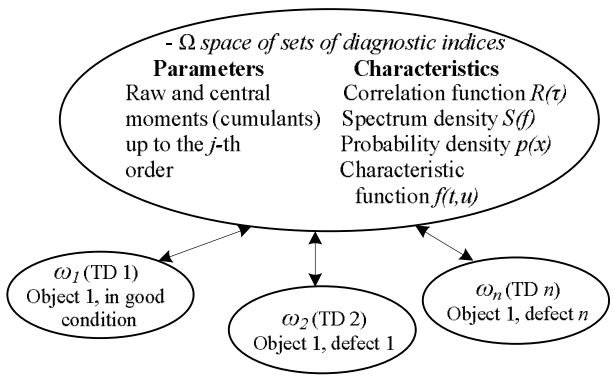

Fig. 1. Principle of formation of sets of diagnostic indices

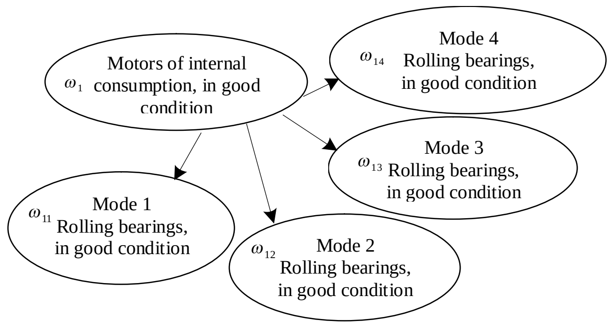

Fig. 2. The schematic of TD formation for 4 operating modes of rolling bearings.

The ω_{21} schematic diagram shown in Fig. 2 depicts the training datasets formed for serviceable rolling bearings, which are parts of motors of internal consumption and operate in 4 different speed modes.

These modes are represented by diagnostic subspaces: ω_{11}, ω_{12}, ω_{13}, ω_{14}. In the same way the formation of diagnostic spaces comprising TD is accomplished for other EE types.

The formed family of diagnostic spaces can be presented in the following matrix form

$$\Omega = \begin{Vmatrix} \omega_{11} & \omega_{12} & \dots & \omega_{1n} \\ \omega_{21} & \omega_{22} & \dots & \omega_{2n} \\ \dots & \dots & \dots & \dots \\ \omega_{k1} & \omega_{k2} & \dots & \omega_{kn} \end{Vmatrix}. \qquad (13)$$

The subspaces located in the matrix (13) rows correspond to the same technical conditions of the unit working in different operating modes of the investigated EE, while the subspaces located in the matrix (13) columns correspond to the operating mode of the unit being in different technical conditions. Therefore, the index $j = \overline{1,k}$ in the family of subsets ω_{nk} designates a certain type of defect, and the index $p = \overline{1,n}$ is designates the operating mode of EE.

Application of Smart Grid conception envisages considerable expansion of possibilities of diagnostics systems owing to realization of additional function, namely, providing of bilateral information exchange between all hierarchical levels of the system, remote monitoring of conditions of the investigated objects of power stations, evaluation of residual capacities, etc. Practical realization of such IMDS requires us to develop appropriate methods, algorithms and software that would process, in real-time regime, measured signal and produce the diagnostic result regarding the technical condition of investigated EE.

4. Conclusions

1. Methods for development of informational support have been proposed; the methods concern the development and investigation of mathematical models of diagnostic signals as well as construction of models for the process of training datasets formation for information-measuring systems of electrical equipment diagnostics.

2. The method of representation of training datasets in the form of a matrix has been proposed; the matrix elements are dispersion ellipses corresponding to both the certain types of defects of specified EE units and its operating modes. This fact accounts for feasibility of functioning of EE IMDS in compliance with Smart Grid conception.

3. The mathematical models of diagnostic signals have been advanced; they take into account both possible defects of tested objects and the modes (speed, electric, temperature mode and other ones) of a working investigated object.

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ОСОБЛИВОСТІ ПОБУДОВИ БАГАТОРІВНЕВИХ СИСТЕМ ТЕХНІЧНОЇ ДІАГНОСТИКИ ЕЛЕКТРИЧНИХ МАШИН

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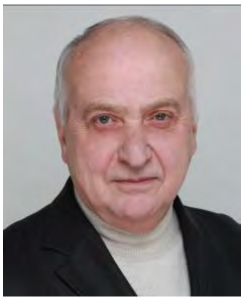
Наведено основні вимоги до систем діагностування електроенергетичного обладнання з урахуванням концепції Smart Grid. Розглянуто деякі результати, що стосуються питань утворення діагностичних сигналів у працюючому електротехнічному обладнанні. Запропоновано інформаційне забезпечення до багаторівневої системи електротехнічного обладнання. Розглянуто основні складові цього забезпечення, серед яких математичні моделі діагностичних сигналів, а також моделі, які характеризують процес формування навчальних сукупностей, що водночас відповідають і певним дефектам досліджуваних вузлів електротехнічного обладнання, і режимам їхньої роботи. Запропоновано й досліджено форми представлення навчальних сукупностей, що відповідають певним технічним станам вузлів електротехнічного обладнання і які можуть працювати у різних режимах.



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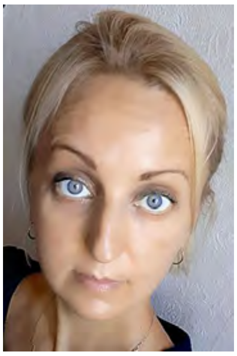

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