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Adaptive Identification Method of a Signal from Stray Magnetic Field Sensor for Turbogenerator Diagnostics

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The topic of this paper is dictated by the necessity to improve the reliability of methods for determining a short circuit of rotor winding with the use of the stray magnetic field sensor installed at the turbogenerator end.

The research objectives are to develop the signal identification models and algorithms based on stray magnetic field sensor data for the diagnostics of a short circuit of rotor winding of synchronous generator.

Theoretical and practical developments in the areas of systems analysis, electrical machines modeling, optimization and linear algebra are used in the paper. The solution is based on theoretical and experimental data from magnetic field sensor installed at the synchronous generator end.

A method of a signal identification and diagnostics from stray magnetic field sensor installed at the synchronous generator end is developed. This method is based on an integrated system of signal models with time-varying parameters and additional a priori information. The method allows for determining the signal local changes from the stray magnetic field sensor caused by the short circuit of rotor winding of the synchronous generator by comparing the original signal with model signal. Experimental data for loaded synchronous generator are considered. It is found that the proposed method provides reliable predictions of the rotor winding damage even for a small number of short circuited coils.

Keywords: identification, adaptation, diagnostics, integrated system of models with variable parameters, a priori information, turbogenerator, short circuit, magnetic field sensor.

Despite the efforts to increase the reliability of turbine generators high probability of their damage still exists [1]. This is because electromagnetic, thermal and mechanical stresses on rotor winding have been increased in the last 50 years.

It is impossible today to increase turbogenerators reliability through routine diagnostics, therefore a lot of attention is paid to the development and refinement of new methods of functional diagnostics [2].

A turn-to-turn short circuit of rotor winding is a widely spread electrical fault and at the same time it is difficult to determine. It is difficult to determine turn-to-turn short circuit winding according to some construction peculiarities. Technologies based on turbine generator internal and applied magnetic field analysis are considered because there is a symmetric configuration of magnetic field around a turbine generator. This configuration immediately depends on the turbine generator rotor winding technical state [3].

At present a lot of machines are operated with sensors installed in the vicinity of rotor or at the turbine generator end [4–6, 10].

The main problems of these diagnostics systems are mathematical interpretation of the sensor signals and turn-to-turn short circuit diagnostic property selection as current in rotor winding changes.

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We present a method for signal adaptive identification from stray field magnetic sensor installed in the synchronous generator end. The method is based on interpretation of experimental data and it is intended for the turn-to-turn short circuit rotor winding diagnostics.

1. A method for turn-to-turn short circuit rotor winding identification and diagnostics

The adaptive identification method of a signal from stray magnetic field sensor for the diagnostics of turn-to-turn short circuit rotor winding is based on a discrete integrated system of $\overset{*}{y}_n$ signal models. They are of the form [7]

$$\begin{cases} \overset{*}{y}_n = y_n + \xi_n = f(t_n, \boldsymbol{\alpha}_n) + \xi_n, \\ \bar{\mathbf{z}}_n = \mathbf{f}_a(y_n, \boldsymbol{\alpha}_n) + \boldsymbol{\eta}_n, n = 1, 2, 3, \dots, \end{cases} \tag{1}$$

where $\boldsymbol{\alpha}_n = (\alpha_j(t_n), j = \overline{1, m})$ is unknown single-valued function of time; $\overset{*}{y}_n, y_n$ are experimental and calculated signal values based on the model $f(t_n, \boldsymbol{\alpha}_n)$; $\mathbf{f}_a(y_n, \boldsymbol{\alpha}_n) = (f_{a,j}(y_n, \boldsymbol{\alpha}_n),\ j = \overline{1, p})$ is the object model with additional a priori data $\bar{\mathbf{z}}_n = (\bar{z}_{k,n}, k = \overline{1, p})$ identified in the time moment t_n; f and $f_{a,j}$ are the known composite functions; $\xi_n, \boldsymbol{\eta}_n = (\eta_j,\ j = \overline{1, p})$ are random values of signal $\overset{*}{y}_n$ errors, additional data and expert analysis errors $\bar{\mathbf{z}}_n$, etc.

The example of model (1) is the following system of equations

$$\begin{cases} \overset{*}{y}_n = y_n + \xi_n = \alpha_{1,n} + \alpha_{2,n} \sin(\alpha_{3,n} t_n) + \xi_n, \\ \bar{\alpha}_{j,n} = \alpha_{j,n} + \eta_{j,n}, j = \overline{1, 3}, n = 1, 2, 3, \dots, \end{cases} \tag{2}$$

where $\bar{\alpha}_{j,n}$ describes a priori information for signal parameters $\alpha_{j,n}$ from magnetic stray field sensor.

A principle of signal adaptive identification method is to replace a multivariable $\boldsymbol{\alpha}(t)$ of signal notation $f(t, \boldsymbol{\alpha}(t))$ to a time-invariant $\boldsymbol{\alpha}(\overset{*}{t})$ of model $f_0(t, \boldsymbol{\alpha}(\overset{*}{t}))$ at a point $\overset{*}{t} \in [t_1, t_n]$:

$$\boldsymbol{\alpha}(t) = \boldsymbol{\alpha}(\overset{*}{t}) \ \text{ where } \ \overset{*}{t} \in [t_1, t_n].$$

Parameters of $\boldsymbol{\alpha}(\overset{*}{t})$ can be determined in terms of data $\overset{*}{y}_i$, $i \in [1, n]$ from the interval $(\overset{*}{t} - \tau) \in [t_1, t_n]$ formed by impulse response $K_h((\overset{*}{t} - \tau)/h)$ with parameter h [8].

Assuming that $\overset{*}{t}$ is equal to t_n, the adaptive parametric identification process (1) can be represented as a successive solution of optimization problems [7, 8]

$$\overset{*}{\boldsymbol{\alpha}}_n(\boldsymbol{\beta}_n, h_n) = \arg\min_{\alpha_n} \Phi(t_n, \boldsymbol{\alpha}_n, \boldsymbol{\beta}_n, h_n), \tag{3}$$

$$\overset{*}{\boldsymbol{\beta}}_n, \overset{*}{h}_n = \arg\min_{\boldsymbol{\beta}_n, h_n} (J_0(\overset{*}{\boldsymbol{\alpha}}_n(\boldsymbol{\beta}_n, h_n))), n = 1, 2, 3, \dots, \tag{4}$$

where $\arg\min_x f(x)$ is a minimum point $\overset{*}{x}$ of the function $f(x)$ $(f(\overset{*}{x}) = \min_x f(x))$; $\Phi(t_n, \boldsymbol{\alpha}_n, \boldsymbol{\beta}_n, h_n) = \Phi(J_0(t_n, \boldsymbol{\alpha}_n), J_a(\boldsymbol{\alpha}_n, \boldsymbol{\beta}_n, h_n))$ is a composed empirical measure of model (1). The functional Φ is represented by a partial measure of signal y_n model:

$$J_0(t_n, \boldsymbol{\alpha}_n) = \sum_{i=1}^{n} K_h((t_n - t_i)/h_n) \psi_0(\overset{*}{y}(t_i) - f(t_i, \boldsymbol{\alpha}_n))$$

and by a partial measure of comparable models

$$J_a(\boldsymbol{\alpha}_n, \boldsymbol{\beta}_n, h_n) = \sum_{k=1}^{p} \beta_{k,n} \psi_{a,k}(\bar{z}_{k,n} - f_{a,k}(y_n, \boldsymbol{\alpha}_n)),$$

where $\overset{*}{\boldsymbol{\alpha}}_n = \overset{*}{\boldsymbol{\alpha}}(t_n)$; $\overset{*}{y}(t_i)$, $i = \overline{1,n}$ is the value of true signal from stray magnetic field sensor at time t_i; $\boldsymbol{\beta}_n = (\beta_{k,n}, k = \overline{1,p})$ is a control parameters vector that determines the additional a priori information; ψ_0, ψ_a are known functions.

It should be noted that (1), (2), (3) and (4) allow us to synthesize a wide range of identification algorithms of $\overset{*}{y}_n$ signal models for linear and nonlinear parameters $\boldsymbol{\beta}_n$ and various quality indicators determined by the functions ψ_0, $\psi_{a,k}$ as well as by the methods for optimization problems solution. For example, successive solution of simultaneous linear algebraic equations with the use of the Newton-Gaussian optimization method, the nonlinear signal model and quadratic quality indicators $\psi_0(x) = \psi_a(x) = x^2$ all add up to the optimization problem (2) to give

$$\begin{cases} \overset{*}{\boldsymbol{\alpha}}_{i,n} = \overset{*}{\boldsymbol{\alpha}}_{i-1,n} + \gamma_{i,n} \Delta \overset{*}{\boldsymbol{\alpha}}_{(i-1),n}, i = 1, 2, 3, ... \\ A_n \cdot \Delta \overset{*}{\boldsymbol{\alpha}}_{(i-1),n} = B_n, n = n_0, n_0 + 1, n_0 + 2, ..., \end{cases} \tag{5}$$

$$A_n = (D_n^T K(h_n) D_n + D_{a,n}^T W(\boldsymbol{\beta}_n) D_{a,n})_{(i-1),n},$$
$$B_n = (D^T K(h_n) \boldsymbol{e}_{0,n} + D_{a,n}^T W(\boldsymbol{\beta}_n) W(\boldsymbol{\gamma}_n) \bar{\boldsymbol{e}}_{a,n})_{i-1},$$

where $D_n = \left(\dfrac{\partial f(t_i, \boldsymbol{\alpha}_n)}{\partial \alpha_{j,n}}, i = \overline{1,n}, j = \overline{1,m} \right)_{n,m}$, $D_{a,n} = \left(\dfrac{\partial f_{a,k}(t_n, \boldsymbol{\alpha}_n)}{\partial \alpha_{j,n}}, k = \overline{1,p}, j = \overline{1,m} \right)_{p,m}$ are partial derivatives matrixes of the signal model from the sensor and object models; $\boldsymbol{e}_{0,n} = (\overset{*}{\boldsymbol{y}}_n - \boldsymbol{f}_0(\boldsymbol{\alpha}_n)$, $\bar{\boldsymbol{e}}_{a,n} = (\bar{\boldsymbol{z}}_n - \boldsymbol{f}_a(y_n, \boldsymbol{\alpha}_n))$ are residual vectors, $\gamma_{i,n}$ is a parameter step; $W(\boldsymbol{\beta}_n) = \mathrm{diag}(\beta_{1,n}, \beta_{2,n}, \dots \beta_{p,n})$ is a diagonal matrix of control parameters; $K(h_n)$ is a diagonal matrix of weighting functions $K((t_n - t_{n-i})/h_n), i = \overline{1, n-1}$.

The analysis of signals from sensor [1–5, 10] shows local changes observed in the area under the turn-to-turn short circuit (see Fig. 1, 2). For example, in the open circuit regime significant changes of the signal from sensor occur in its maximum value region (Fig. 1). Changes occur in minimum value regions of the sensor signal when generator is loaded (see Fig. 2, area is highlighted by a dashed oval).

In the open circuit regime it is appropriate to use a deviation measure of the actual sensor signal value $\overset{*}{y}_i$

$$J_1 = \sum_{i=k}^{m} \left| \overset{*}{y}_i - f(t_i, \overset{*}{\boldsymbol{\alpha}}_i(\overset{*}{\boldsymbol{\beta}}_n, \overset{*}{h}_n)) \right| \leqslant \varepsilon_1, \ t_i \in \Delta t_{k,m}, \tag{6}$$

where $\Delta t_{k,m} = t_m - t_k$, $\Delta t_{k,m} \in [t_1, t_n]$, $\overset{*}{\boldsymbol{\alpha}}_n(\overset{*}{\boldsymbol{\beta}}_n, \overset{*}{h}_n)$ are model parameters (2) and $\overset{*}{\boldsymbol{\beta}}_n, \overset{*}{h}_n$ are control parameters. For a loaded generator criterion (6) takes the form

$$J_2 = \sum_{i=n}^{n_k} \left| \overset{*}{y}_i - \overset{*}{\alpha}_1(\overset{*}{\boldsymbol{\beta}}_n, \overset{*}{h}_n)) \right| \leqslant \varepsilon_2, \ t_i \in \Delta t_{n_k}. \tag{7}$$

When turn-to-turn short circuit is observed then criteria (6) and (7) are not fulfilled.

2. Evaluation of diagnostics models and algorithms

The results of an investigation into algorithms for signal adaptive identification (2, 3, 4) and turn-to-turn short circuit rotor winding diagnostics (6) are shown in Fig. 1, 2 and in Tab. 1.

Fig. 1 shows the input (curve 1) and recovery (curve 2) data based on the model of signal identification from stray magnetic field sensor in the open circuit regime without rotor damage and when the 14 % of a number of all coils are turn-to-turn short circuited.

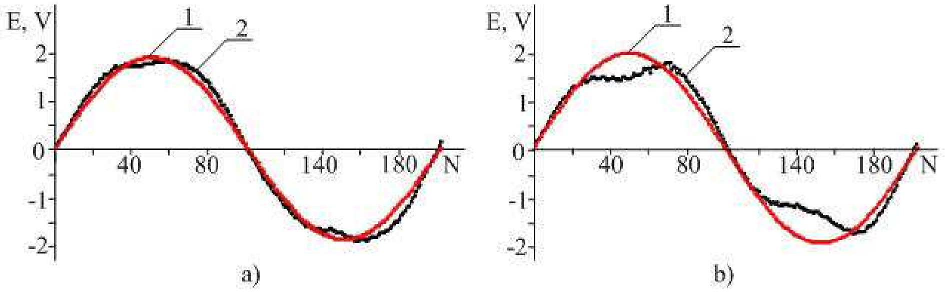

Fig. 1. The input (curve 1) and recovery (curve 2) signal data based on the model of signal identification from stray magnetic field sensor in the open circuit regime: a) without rotor damage; b) 14 % of a number of all coils are turn-to-turn short circuited

Fig. 2 shows the similar results for the synchronous loaded generator.

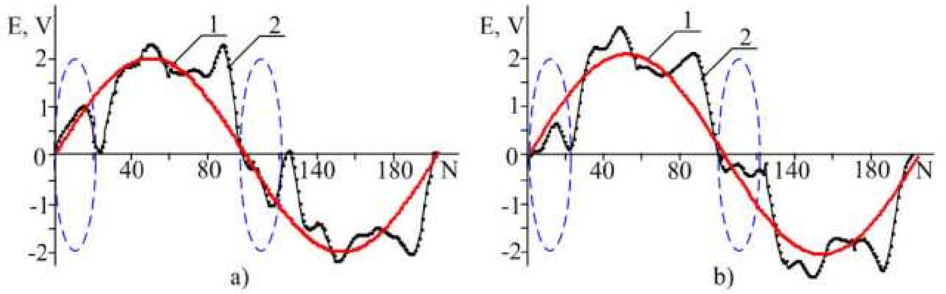

Fig. 2. The input (curve 1) and recovery (curve 2) signal data based on the model of signal identification from stray magnetic field sensor for the loaded generator: a) without rotor damage; b) 3.66 % of a number of all coils are turn-to-turn short circuited

The recovered values of stray magnetic field sensor signal (Fig. 1, 2, curve 2)

$$\hat{y}_n = \overset{*}{\alpha}_{1,n}(\overset{*}{\beta}_n,\ *h_n) + \overset{*}{\alpha}_{2,n}(\overset{*}{\beta}_n,\ *h_n)\sin(\overset{*}{\alpha}_{3,n}(\overset{*}{\beta}_n, \overset{*}{h}_n)t_n), \quad (8)$$

are obtained with the use of model (2) and algorithm (4). The respective values of partial differential coefficients are

$$\frac{\partial f(t_i, \boldsymbol{\alpha}_n)}{\partial \alpha_{1,n}} = 1, \ \frac{\partial f(t_i, \boldsymbol{\alpha}_n)}{\partial \alpha_{2,n}} = \sin(\alpha_{3,n} t_i), \ \frac{\partial f(t_i, \boldsymbol{\alpha}_n)}{\partial \alpha_{3,n}} = \alpha_{3,n}\cos(\alpha_{3,n} t_i).$$

The weight function is $K((x/h) = \exp(-x^2/h)$, the matrix of additional a priori information is $D_{a,n} = \mathrm{diag}(\mathbf{I})_{3,3}$ and control parameters matrix is $W(\boldsymbol{\beta}_n) = \beta_n \mathrm{diag}(\mathbf{I})_{3,3}$. Parameters $\overset{*}{\beta}_n$ and $\overset{*}{h}_n$ are calculated from a solution of optimization problem (3), using the quadratic quality index $\psi_0(x) = x^2$. The deformed polyhedron method [9] was used at regular intervals with $n = 50, 100, 150, \ldots$. Values of model parameters from the sensor $\bar{\alpha}_{j,n} = \overset{*}{\alpha}_{1,n}(0, \overset{*}{h}_n)$, $j = \overline{1,3}$ and $n = 50$ are used. The additional information

$$\overset{*}{y}_n = \alpha_{1,n} + \alpha_{2,n} \sin(\alpha_{3,n} t_n) + \xi_n$$

is obtained without the use of a priori information, with further scheme correction

$$\bar{\alpha}_{j,n_k} = \overset{*}{\alpha}_{j,n_{(k-1)}}(\overset{*}{\beta}_n, \overset{*}{h}_n),\ k = 2, 3, \ldots .$$

Tab. 1 shows diagnostic criteria values (6), (7) based on experimental data (see Fig. 1, 2) (6) without the rotor winding damage and when 3.66 % and 14 % of a number of all coils are turn-to-turn short circuited. Symbols A and B show the obtained criterion value (6) for positive (A) $\overset{*}{y}_i,\ i = \overline{40, 60}$ and for negative (B) $\overset{*}{y}_i,\ i = \overline{140, 160}$ phases, according to the region of maximum signal from the sensor. Symbols C and D show similar results for criterion value (7). Symbol C corresponds to the region of minimum value signal at the beginning of the half-period for the positive phase $\overset{*}{y}_i$, $i = \overline{1, 20}$ and symbol D corresponds to the region of minimum value signal at the beginning of the half-period for the negative phase $\overset{*}{y}_i$, $i = \overline{80, 100}$.

Table 1. The results of the synchronous generator diagnostics

Rotor winding	Diagnostic criteria value (6)			
	Idle generator		Loaded generator	
	A	B	C	D
Without damage	0.24	0.23	2.17	2.08
With 3.66 % of a number of all coils are turn-to-turn short circuited	0.45	0.41	2.64	2.56
With 7 % of a number of all coils are turn-to-turn short circuited	1.43	0.89	3.04	3.12
With 14 % of a number of all coils are turn-to-turn short circuited	1.61	2.01	3.58	3.62

The table shows that there is a significant change in the quality indicators (6) and (7) when the turn-to-turn short circuit occurs. This provides a reliable way to diagnose the turn-to-turn short circuit of rotor winding.

3. Conclusion

1. We propose the signal identification and diagnostics method that uses data from stray magnetic field sensor installed at the synchronous generator end. This method is based on the integrated system of signals models with time-varying parameters that use additional a priori information.

2. The diagnostics method allows one to determine a signal local variation from stray magnetic field sensor by comparing the original signal with model signal. The variation occurs due to changes in the synchronous generator state caused by the turn-to-turn short circuit of rotor winding.

3. Experimental data for loaded synchronous generator and for synchronous generator in the open circuit regime are used. It is shown that the proposed method predicts rotor winding damage even when only 3.66 % of a number of all coils are turn-to-turn short circuited.

4. The advantages of the method: the model and algorithm of signal identification use data from stray magnetic field sensor, the turbogenerator rotor winding diagnostics is based on integrated system models with time-varying parameters, a priori information and method correction, the training interval volume is used for the adaptive identification process.

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Метод адаптивной идентификации сигнала с датчика магнитного поля рассеяния для диагностики турбогенератора

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Актуальность работы обусловлена необходимостью повышения надежности методов определения виткового замыкания обмотки ротора турбогенератора с датчиком магнитного поля рассеяния, установленного в его торцевой зоне. Цель исследования: разработка метода, моделей и алгоритмов идентификации сигналов с датчика магнитного поля рассеяния для диагностики виткового замыкания обмотки ротора синхронного генератора.

Методы исследования: использованы теоретические и практические разработки в области *системного анализа, моделирования и идентификации электрических машин, методов оптимизации функций и линейной алгебры. Решение задач проводилось теоретически и на основе экспериментальных данных, полученных на выходе датчика магнитного поля, установленного в торцевой зоне синхронного генератора.*

Результаты: метод идентификации и диагностики сигналов с датчика магнитного поля рассеяния, установленного в торцевой зоне синхронного генератора, основанный на интегрированной системе моделей сигналов с переменными во времени параметрами с учетом и корректировкой дополнительной априорной информации. Метод позволяет определять локальные изменения сигнала с датчика магнитного поля рассеяния, вызванные замыканием обмотки ротора синхронного генератора, путем сравнения исходного сигнала с его моделью. На основе экспериментальных данных нагруженного синхронного генератора и на холостом ходу показано, что предложенный метод диагностики обеспечивает достаточно надежное выявление повреждения обмотки ротора, начиная с 3.66 % короткозамкнутых витков.

Ключевые слова: идентификация, адаптация, диагностика, интегрированные системы моделей с переменными параметрами, априорная информация, турбогенераторы, витковые замыкания, датчик магнитного поля.