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Principal Component Analysis for Electromagnetic Drives Technological Production Process Control

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Abstract: This study describes the implementation of principal component analysis method for electromagnetic drives technological production process control. The analysis of existing methods of technological processes of production of proportional electromagnetic drives is performed. The method for control of technological production process is developed. The approximation of dynamic magnetization characteristic of electromagnetic drives is made. Projecting of dynamic characteristic of the magnetization by method of principal component analysis is implemented. The calibration and classification methods are selected. To separate the training sample into groups and classification of dynamic characteristic of the magnetization for the test sample was used method of formal independent modeling of class analogies. The results of implementation of selected methods are presented.

Key words: Dynamic characteristic magnetization, process control, the principal component analysis, proportional electromagnetic, actuator

INTRODUCTION

An important element in the process of proportional electromagnetic drives production is to identify deviations from the nominal mode of its occurrence (Espinosa *et al*., 2008; DUlk and Kovacshazy, 2015; Xu and Tang, 2015). In connection with this urgent task is to develop a methods for process control will determine the place and the degree of deviation from the nominal values of the process conditions for further management (Shaykhutdinov *et al*., 2015a-d). In the production of the proportional magnets, like other electrical devices, uses various technological operations of general engineering: black and non-ferrous casting, forging all kinds of machining all kinds of welding, soldering, forging, heat treatment, electroplating coating, assembly, painting and a number of specific technological operations that are unique to the electrotechnical equipment (Murphy, 2012; Kotelenetc *et al*., 2003). In this connection to analyze the quality of the process flow of the manufacturing process of proportional solenoids it is necessary to control the parameters of various physical nature mechanical, electrical, magnetic. To implement the quality management process is important not only to establish the fact of marriage but also to identify the type and place of origin. Information about the type of marriage will determine the place of its occurrence on the production line and in a timely manner to correct the process.

Statistical process control is to identify non-random process violations while the control action (correction process) is applied when the manufactured products still meet the specifications but some statistical indicators give reason to assume the existence of a non-random causes that lead to the disruption of the process. Process control is to identify and eliminate these causes. Variability due to accidental causes can be reduced only by improving the process. Currently there are two common approaches to this task. The first of them is the rejection of articles on the “fit-unfit” by using control charts. Control charts-a tool that allows you to track the progress of the process flow and work on it preventing its deviation from the requirements imposed on the process (Antonov, 1982; Gerasimov, 2012). If there is a violation of the manufacturing process of the signal must be identified and eliminated the cause of violations but checklists failed to detect the type of defect. The second most used method of process control is based on comparing the measured electrical, magnetic or mechanical energy with exemplary. This approach involves the use of their means of measurement for each of the measured characteristics

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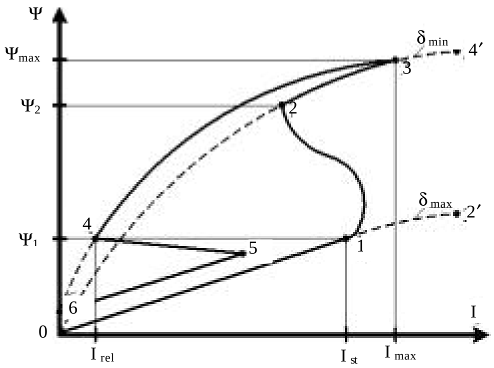

Fig. 1: The dynamic characteristic of the magnetization of the electromagnetic actuator

which makes it difficult to control the process and time consuming. As well as checklists method allows to separate from the marriage of good products but the determination of the causes and the type of marriage is extremely difficult. Another currently used method for the detection of a marriage is a method based on a comparison of the measured electric, magnetic or mechanical energy with exemplary performance during the final inspection. The main characteristics are regulated:

- Static traction characteristics $F = f(\delta)$
- Dynamic traction characteristics $F_d = f(\delta)$
- The movement of anchor in time $\delta = f(t)$
- The current in the coil in time $i = f(t)$
- Heating and cooling in time $\Theta = f(t)$
- The dependence of the magnetic flux from current $\Phi = f(i)$ for fixed values of the gap δ

For process control these characteristics are not suitable and getting them-it is a long laborious process. This situation encourages the search for integral characteristics that allow to obtain information for process control in a short (no >1-2 min) time. Gordon and Slivinskaia (1960), Slivinskaia (1972) and Kovalev (2001) have shown that having a Dynamic Characteristic of the Magnetization (DCM) of the electromagnetic drive (Fig. 1) can be calculated most of the characteristics regulated by state standards. As a result it can be concluded that the dynamic characteristic magnetization latent contains information about most of the electromagnetic drive parameters. Thus, it can be determined knowing the towing the time and energy parameters therefore the dynamic magnetization characteristic can be used as an integral characteristic of the electromagnetic actuator. Despite all its advantages the dynamic characteristic of the magnetization has a complex shape, making it difficult to determine the type of defects.

MATERIALS AND METHODS

The first step of the method of manufacturing process control of proportional solenoids is to obtain the characteristics of containing information about the technical parameters depend on the mode of the process. The definition of such characteristics should be carried out on the fully assembled product and be low-cost in terms of time and technical resources. Analysis of proportional solenoids, conducted in the first chapter has shown that this is an integral characteristic of the dynamic characteristics of the magnetization. It carries information about the magnetic, electrical, traction and dynamic properties of proportional solenoids and to obtain it can be used in so-called "no sensor" devices. It does not require disassembly of the test product and the working coil currents flow equivalent to the nominal.

As described earlier as an integral characteristic for the quality analysis is selected electromagnetic drive DCM. Its use as an array of pairs of points flux current for further processing difficult. The use of large amounts of data (one DCM measured with an accuracy of up to 3% contains about 15.000 pairs of points) places high demands on the performance and processing facilities increases the time of the operation process control. In connection with this approximation is often used this characteristic expression describing each section of DCM. piecewise approximation method is to replace the given nonlinear DCM 6 curves describing the type of polynomials:

$$y = \sum_{1}^{m} k_n x^n + b$$

Where:

k_n = Coefficients describing the slope of the curve and the bends

b = Coefficient describing the displacement of the curve with respect to the x-axis

m = The maximum degree of the polynomial

Such a replacement non-linear characteristic allows calculation analytically using linear equations and if necessary to determine the required number of points DCM. For clarity we will continue to use only the descending branch of the DCM, i.e., sections 0-1, 1-2 and 2-3 on Fig. 1. Because of the ambiguity of DCM (one value of current response may take several flow values), depending on the use it as $\Phi(i)$ (Fig. 2) is not appropriate. This problem is solved by using reverse characteristics $i(\Phi)$ (Fig. 3). The first and second portions can be described first degree polynomial. The first comes from the origin of the coordinate system, hence the coefficient b = 0:

$$y^{(1)} = K_1^{(1)} x$$

and the second portion has the form:

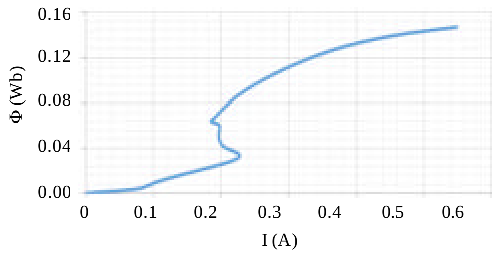

Fig. 2: The dynamic characteristics of the magnetization in the space of two principal components

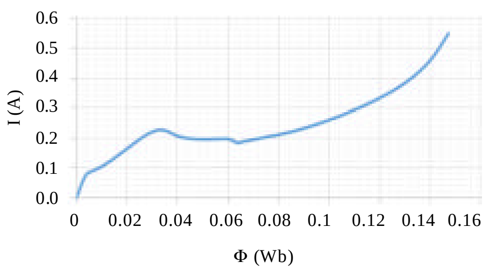

Fig. 3: DCM type i(Φ) of conditioned proportional solenoid

$$y^{(2)} = k_1^{(2)}x + b^{(2)}$$

The third portion may be described by a polynomial of the second or third degree:

$$y^{(3)} = k_1^{(3)}x + k_2^{(3)}x^2 + b^{(3)}$$
$$y^{(3)} = k_1^{(3)}x + k_2^{(3)}x^2 + k_3^{(3)}x^3 + b^{(3)}$$

Figure 4 shows the DCM 1 with the approximation of the third portion of the second and third degree. The error in the application of the second degree was 8% and the application of the third degree polynomial does not exceed acceptable for magnetic measurements 3%. To determine the error of approximation are the differences between the original and approximating characteristics. The method of finding approximation error (Antonov *et al*., 1986; Lankin and Lankin, 2015) is illustrated in Fig. 5. In the original $\Phi_1(I)$ next set of points which build the perpendiculars to the intersection with the approximating characteristic $\Phi_2(I)$. The absolute error of the magnetic flux Φ and current I at each test point is defined as the projection of prisoners intervals between model and measured characteristics ΔΦ and ΔI on the coordinate axes. The relative error of the current I and magnetic flux Φ as well as complete measurement error of characteristics determined by the expressions:

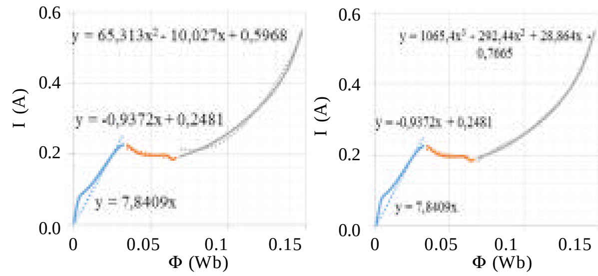

Fig. 4: Approximated DCM 1 type Φ(i)

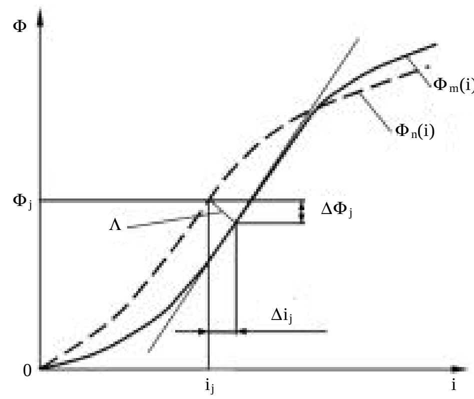

Fig. 5: The method of finding approximation error

$$\delta_I = \frac{\Delta I}{I}$$
$$\delta_\Phi = \frac{\Delta \Phi}{\Phi}$$
$$\delta = \sqrt{\delta_I^2 + \delta_\Phi^2}$$

From these results and the selected maximum is taken as the approximation error. As an example, consider the DCM proportional solenoids with a variety of technological deviations from the nominal value using the approximation of the third portion DCM third-degree polynomial. The form of these characteristics is shown in Fig. 6. Thus to describe the ascending branch of the DCM (sections 0-1, 1-2, 2-3) needed seven coefficient values approximating polynomial and four values that define the point of the connection sections 0-1, 1-2 and 2-3. This fact shows that the device to definition DCM should have presentation DCM in the form of approximating polynomials. Due to the fact that the dynamic characteristics of the magnetization proportional solenoid contains latent information on the majority of its parameters it is difficult not unambiguous, making it difficult to analyze in order to identify the information required to generate control signals process. Therefore, the second step is to reduce the dimension of the analyzed information.

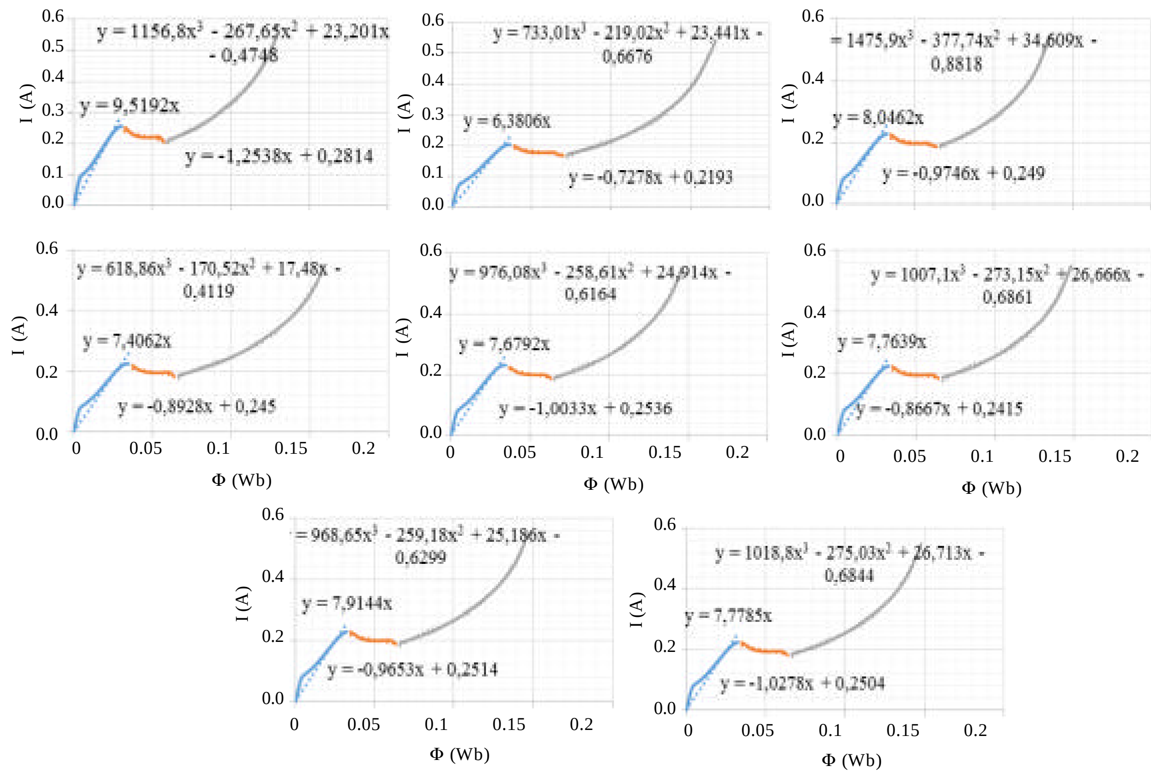

Fig. 6: DCM of proportional solenoids with technological deviations from the nominal value: a) DCM 2; b) DCM 3; c) DCM 4; d) DCM 5; e) DCM 6; f); DCM 7; g); DCM 8 and h) DCM 9

To reduce the dimension of the analyzed information currently finds application approach using the projection method of the principal component (GC) to reduce the dimension of the analyzed information (Shayhutdinov *et al*., 2015 a-d; Esbensen, 2003). The essence of the method of principal component consists of a transition from the original variables to new values the main components of which are linear combinations of the original variables with the maximum possible dispersion. In this first principal component has the maximum variance is normalized by a linear combination of all possible signs of starting and the second-takes into account the maximum value and the remaining correlation variance is not associated with the first component and so on up to n (n-number of principal component).

Consider the use of principal component of the group comprising K DCM proportional electromagnetic drives. The coordinates of the points $i(\Phi)$ by virtue of their dependence on many technological regimes and not considered random noise as well as the presence of the random component of the measurement error, can be considered as random variables. Accordingly, the coordinates of the points of each DCM will be regarded as a vector. In the original curve n choose fixed values of the magnetic flux $\Phi_d = d\Delta\Phi$:

$$\Delta\Phi = \Phi_{max}/n$$

Where:

Φ_{max} = Maximum possible flow value for all studied characteristics
n = Selected number of fixed flux values
d = Point number.

Defines the value of the currents $i_1(\Phi_d)$ which are the elements formed by the vector I_1:

$$I_1 = \begin{bmatrix} i_1(\Phi_1) \\ i_1(\Phi_2) \\ \dots \\ i_1(\Phi_d) \\ \dots \\ i_1(\Phi_n) \end{bmatrix}$$

Similarly, the vectors formed for other DCM with current values i defined for the same fixed values of flux Φ_d. Here it should be noted that the use of piecewise approximation to DCM enables us to calculate the missing values by interpolation vectors $i_j(\Phi_d)$, if $\Phi_{jmax}<\Phi_{max}$. The thus obtained vectors stored in a matrix I dimensionality $n\times k$ where n the number of recorded pixels and k the number of the test curves:

Table 1: Types of defects in the test of proportional solenoids

Number DCM	Kind of technological deviations from the nominal value	The maximum value of the magnetic flux (Wb)
1	Without technological deviations	0.147
2	In 10% of the nominal amount of reduced operating winding turns	0.110
3	In 10% of the nominal amount of increased operating winding turns	0.184
4	In 10% of the nominal value reduced saturation magnetic induction armature material	0.136
5	In 10% of the nominal value increased saturation magnetic induction armature material	0.158
6	In 10% of the nominal value reduced saturation flux density of the magnetic yoke material	0.146
7	In 10% of the nominal value increased saturation induction of the magnetic yoke material	0.148
8	In 10% of the nominal value reduced saturation flux density of the magnetic body material	0.147
9	In 10% of the nominal value increased saturation induction of the magnetic body material	0.148

$$I = \begin{bmatrix} i_1(\Phi_1) & i_2(\Phi_1) & \cdots & i_j(\Phi_1) & \cdots & i_k(\Phi_1) \\ i_1(\Phi_2) & i_2(\Phi_2) & \cdots & i_j(\Phi_2) & \cdots & i_k(\Phi_2) \\ \vdots & \vdots & & \vdots & \vdots & \vdots \\ i_1(\Phi_d) & i_2(\Phi_d) & \cdots & i_j(\Phi_d) & \cdots & i_k(\Phi_d) \\ \vdots & \vdots & & \vdots & & \vdots \\ i_1(\Phi_n) & i_2(\Phi_n) & & i_j(\Phi_n) & & i_k(\Phi_n) \end{bmatrix}$$

To find the covariance define the vector of sample means the rows $\overline{Id}$. The next step is determined deviations from the mean for each observation, and we reduce the variation in the matrix F wherein each element is formed by the following Equation:

$$f_{di} = I_j(\Phi_d) - \overline{I_d},\ d = 1 \div n,\ j = 1 \div k$$

Since, the value of the number n of observations is limited, it is possible to find only an estimate of the covariance S:

$$S = \frac{FF^T}{k-1}$$

Let us find the vector of characteristic values $\mathbf{\Lambda}$ and an array of characteristic vectors **B** of matrix S. Using these matrices we find Principal Component (PC). Given the fact that in contrast to the 2 considered as an example of random variables with a two-dimensional density function the dimension of the space in which the point spread matrix I = to the number of rows of the matrix, i.e., n:

$$Z = B^T I$$

The dimension of the matrix obtained is the same as that of the matrix I:

$$Z = \begin{bmatrix} Z_{11} & Z_{12} & \cdots & Z_{k1} \\ Z_{12} & Z_{22} & \cdots & Z_{k2} \\ \vdots & \vdots & & \vdots \\ Z_{I1} & Z_{21} & \cdots & Z_{k1} \\ \vdots & \vdots & & \vdots \\ Z_{In} & Z_{2n} & & Z_{kn} \end{bmatrix}$$

PC thus obtained are arranged in accordance with the importance that ascending the corresponding eigenvalues. Not all of the PC are important so discard in significant l, leaving only (n-l) component. Thus, after the said transformation matrix Z and B are as follows:

$$Z = \begin{bmatrix} Z_{11} & Z_{12} & \cdots & Z_{k1} \\ Z_{12} & Z_{22} & \cdots & Z_{k2} \\ \vdots & \vdots & & \vdots \\ Z_{1n-1} & Z_{2n-1} & \cdots & Z_{kn-1} \end{bmatrix}$$

$$B = \begin{bmatrix} \beta_{11} & \beta_{21} & \cdots & \beta_{n1} \\ \beta_{12} & \beta_{22} & \cdots & \beta_{n2} \\ \vdots & \vdots & & \vdots \\ \beta_{1n-1} & \beta_{2n-1} & \cdots & \beta_{n-1} \end{bmatrix}.$$

The total dimension of the resulting matrix for sufficiently large 1 is less than the dimension of the original matrix I. Thus the results of this step we get a new space of principal components each of which represents a point of DCM particular product. As an example of projecting DCM 1-DCM 9 in the space PC. At the beginning of the current form the initial matrix I. To do this with the values of the coefficients of the approximating polynomials for each DCM use the following approach: set the maximum value $\mathbf{\Phi}_{max}$ = 0.185 Wb and the number of recorded points n = 43, find $\mathbf{\Delta\Phi}$ and calculate the current value $i_j(\Phi_d)$ (Table 1). When choosing the number of recorded points n, proceed from the assumption that the maximum level of use for the piecewise approximation DCM for regulated GOST measurement error of 3% is three. Thus for any part of DCM is necessary to have at least four of recorded pixels and given the number of sites n must be at least twelve.

Table 2 shows the values of the matrix of currents I for DCM1-DCM9 and in Table 3. the values calculated corresponding PC Z. Figure 7 and Table 4 shows the dependence of the dispersion amount described PC used. The table shows that it is sufficient to use only 2 of the PC so as to further increase their number hardly increases the dispersion described. Figure 8 shows the resulting space of principal components where each point is a projection of one of the original DCM. The

Table 2: The values of the magnetic flux and the current DCM 1-9

	Current (A)								
Magnetic flux (Wb)	DCM 1	DCM 2	DCM 3	DCM 4	DCM 5	DCM 6	DCM 7	DCM 8	DCM 9
0	0	0	0	0	0	0	0	0	0
0.005	0.039	0.048	0.032	0.040	0.037	0.038	0.039	0.040	0.039
0.01	0.078	0.095	0.064	0.080	0.074	0.077	0.078	0.079	0.078
0.015	0.118	0.143	0.096	0.121	0.111	0.115	0.116	0.119	0.117
0.02	0.157	0.190	0.128	0.161	0.148	0.154	0.155	0.158	0.156
0.025	0.196	0.238	0.160	0.201	0.185	0.192	0.194	0.198	0.194
0.03	0.235	0.286	0.191	0.241	0.222	0.230	0.233	0.237	0.233
0.035	0.215	0.333	0.223	0.215	0.214	0.269	0.211	0.218	0.214
0.04	0.211	0.231	0.255	0.210	0.209	0.213	0.207	0.213	0.209
0.045	0.206	0.225	0.187	0.205	0.205	0.208	0.203	0.208	0.204
0.05	0.201	0.219	0.183	0.200	0.200	0.203	0.198	0.203	0.199
0.055	0.197	0.212	0.179	0.195	0.196	0.198	0.194	0.198	0.194
0.06	0.192	0.206	0.176	0.191	0.191	0.193	0.190	0.193	0.189
0.065	0.187	0.220	0.172	0.186	0.187	0.188	0.185	0.189	0.184
0.07	0.183	0.235	0.168	0.196	0.188	0.195	0.188	0.195	0.187
0.075	0.203	0.248	0.168	0.212	0.201	0.209	0.202	0.210	0.202
0.08	0.216	0.261	0.181	0.225	0.212	0.221	0.215	0.222	0.214
0.085	0.228	0.274	0.193	0.237	0.222	0.232	0.225	0.233	0.225
0.09	0239	0.289	0.202	0.249	0.231	0.243	0.236	0.244	0.235
0.095	0.250	0.306	0.211	0.262	0.240	0.253	0.245	0.254	0.245
0.1	0.261	0.326	0.219	0.278	0.250	0.265	0.256	0.266	0.255
0.105	0.273	0.350	0.228	0.296	0.260	0.278	0.268	0.279	0.268
0.11	0.288	0.378	0.236	0.319	0.271	0.294	0.283	0.294	0.282
0.115	0.306	0.413	0.246	0.347	0.284	0.313	0.300	0.312	0.300
0.12	0.327	0.454	0.258	0.382	0.300	0.336	0.321	0.334	0.321
0.125	0.353	0.503	0.272	0.425	0.317	0.363	0.346	0.361	0.347
0.13	0.384	0.560	0.289	0.476	0.338	0.396	0.377	0.392	0.379
0.135	0.422	0.626	0.309	0.537	0.363	0.435	0.413	0.430	0.416
0.14	0.466	0.702	0.333	0.610	0.391	0.481	0.457	0.474	0.460
0.145	0.518	0.789	0.361	0.694	0.424	0.535	0.508	0.526	0.512
0.15	0.579	0.887	0.395	0.792	0.462	0.596	0.567	0.586	0.573
0.155	0.649	0.999	0.433	0.903	0.505	0.667	0.635	0.654	0.642
0.16	0.729	1.124	0.478	1.031	0.554	0.747	0.713	0.732	0.722
0.165	0.820	1.263	0.530	1.175	0.610	0.838	0.801	0.821	0.812
0.17	0.923	1.418	0.589	1.336	0.672	0.941	0.901	0.920	0.914
0.175	1.039	1.588	0.656	1.516	0.742	1.055	1.013	1.032	1.028
0.18	1.167	1.776	0.730	1.716	0.819	1.182	1.137	1.155	1.155
0.185	1.310	1.981	0.814	1.938	0.904	1.322	1.275	1,292	1.295

Table 3: PC values for 1-DCM 1 - DCM 9

No. of DCM/PC	PC 1	PC 2×10^2	PC 3×10^2	PC 4×10^2	PC 5×10^3	PC 6×10^3	PC 7×10^3	PC 8×10^3	PC9×10^3
1	-0.99990	-0.864	0.919	-0.627	1.070	1.563	1.597	0.107	-0.057
2	-0.99928	-2.184	-2.755	1.440	-1.616	1.284	-0.012	0.050	0.018
3	-0.99849	4.793	2.382	1.216	-1.824	0.124	-0.002	-0.022	0.006
4	-0.99923	-3.755	1.029	0.031	-3.765	-2.362	0.277	0.211	0.042
5	-0.99864	4.379	-2.664	-0.931	-1.153	-0.976	0.178	0.261	0.028
6	-0.99995	-0.325	-0.200	0.570	7.422	-1.423	0.035	-0.084	-0.006
7	-0.99993	-0.755	0.691	-0.650	0.587	0.954	-0.671	-0.092	0.445
8	-0.99998	-0.368	-0.195	-0.538	-1.386	-0.029	-0.279	-0.969	-0.189
9	-099910	-0.913	0.793	-0.510	0.658	0.864	-1.123	0.538	-0.286

Table 4: Dependence described dispersion of the number of used PC

No. of PC	Describes the dispersion (%)
1	91.009397
2	99.993659
3	99.997656
4	99.999389
5	99.999920
6	99.999986
7	99.999996
8	99.999999
9	99.99999968

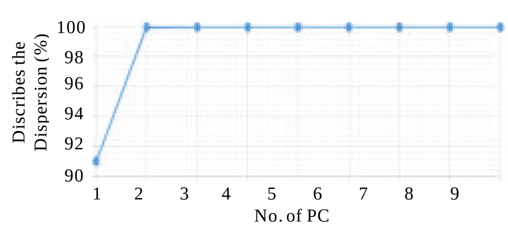

Fig. 7: Describes the dispersion as number of PC

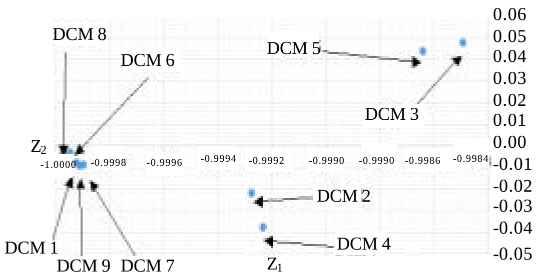

Fig. 8: Projections DCM measured in space PC

problem of the technological control includes the need to develop control signals for equipment production line in order to adjust the production process in the case of its violation. Obviously, conditioning products do not carry information about deviations in the process therefore, should be selected for the analysis of products with differing from the conditioned. However, due to process deviations causes two types. One group of causes connected with the peculiarities of the process-tool wear, loose, change the coolant temperature. Those non-random causes of variation can be eliminated by setting up the equipment. Another group of reasons-unavoidable, accidental causes variability (fluctuations in ambient temperature, variation of material characteristics, etc.). The technological process is preferably carried out so that the quality characteristics of the volatility was caused only by accidental causes. Non-random causes of process variability can be detected with the help of statistical methods. If in the process of production of proportional solenoids are rare (1-5%) the deviation their causes are more likely to be attributed to chance. If there are persistent (>5%) the deviation of the process of production they are considered to be non-random and required hardware configuration by means of control signals. Thus, collecting statistics about the frequency of occurrence and form deviations of the technical parameters of the decision on the need to adjust the mode of production. To implement such an approach must be made on the classification of products and conditioning products with deviations of parameters. In this case it is not about grading or output control and the identification of the most "informative" study containing the information necessary to generate control signals.

Under the classification of products will change the procedure of allocation of groups of products with technical specifications is disconnected from the nominee but not beyond tolerances. To do this efficiently applied to DCM projected in principal component space is one of discrimination methods. Further, detection of stable deviation of the process is necessary to make the management of technological equipment but this requires not only information about the nonconformity in products but also the numerical values of the deviations of technological parameters of manufacturing production process. To do this use the proposed calibration method. The essence of calibration methods is to establish a quantitative relationship between the variables x (DCM point coordinates matrix of projected into the space of the principal components for products from the training sample, recognized substandard) and the response y (matrix of parameter values that characterize the technological process of manufacturing modes of proportional solenoids), depending:

$$y = f(x_1, x_2, x_3,... |a_1, a_2, a_3,....) + \varepsilon$$

Where:

$f(x_1, x_2, x_3,...$ $\|a_1,a_2,a_3,...)$	=	Component bearing latent information of the signs of object
ε	=	Component carrier information noise (random noise, random components of measurement error)

In practice this means estimate the unknown parameters a_1, a_2 a_3 ... in the calibration curve. Thus defining the parameter values a_1, a_2, a_3, ... on the training set and substituting the values of the principal components of the test product can determine the numerical values of the parameters characterizing the modes of technological process in the manufacture of investigational proportional solenoid control action and develop corrective work process equipment.

Thus, the technological control method involves four basic steps. The first step is measured dynamic response of the magnetization of the electromagnetic drive because it contains latent information on the majority of the electromagnetic parameters of the drive. Due to the fact that the dynamic characteristics of the magnetization of the electromagnetic actuator has a complex character is not unique in the second step we reduce the dimension of the analyzed data using the projection method. In the third step is carried out by classification groups measured characteristics to highlight products that carry information on sustainable production process deviations proportional solenoids. In the final step the numerical values are determined by deviations from the normal process with the help of calibration.

RESULTS AND DISCUSSION

Consider the most common calibration methods and analyze the claims put forward taking into account (Lunde *et al*., 2015). Requirements have been put forward:

Table 5: The parameters of proportional electromagnetic drive used for training

No. of DCM	The number of turns of the winding (%) of nominal	Saturation magnetic induction armature material (%) of nominal	Saturation induction of the magnetic material Yoke (%) of the nominal value	Saturation induction magnetic body material (%) of nominal
1	100	100	100	100
2	100	80	80	80
3	100	120	120	120
4	100	110	110	110
5	100	90	90	90
6	80	100	100	100
7	120	100	100	100
8	90	100	100	100
9	110	100	100	100
10	100	80	100	100
11	100	90	100	100
12	100	110	100	100
13	100	120	100	100
14	100	100	80	100
15	100	100	90	100
16	100	100	110	100
17	100	100	120	100
18	100	100	100	80
19	100	100	100	90
20	100	100	100	110
21	100	100	100	120
22	80	80	80	80
23	90	80	80	80
24	110	80	80	80
25	120	80	80	80
26	80	90	90	90
27	90	90	90	90
28	110	90	90	90
29	120	90	90	90
30	80	110	110	110
31	90	110	110	110
32	110	110	110	110
33	120	110	110	110
34	80	120	120	120
35	90	120	120	120
36	110	120	120	120
37	120	120	120	120
38	100	90	110	110
39	100	110	90	110
40	100	110	110	90
41	100	90	120	100
42	100	90	100	120

- Calibration should not lead to an underestimation or overestimation which lead to additional errors
- It must be possible to use multiple response matrix values
- The method shall take into account multicollinearity as dynamic characteristic is complex and its constituent terms are correlated with each other
- It is necessary to use the least amount of PC to simplify the task
- The method should allow calibration with the lowest values of systematic deviations

Most suitable for solving this problem were regression methods to latent structures and regression on principal components because they take into account the phenomenon multicollinearity in the matrix x and give the most accurate solution of the problem. Since method regression is used to latent structures fewer PC for the same result as when using Principal Component Regression it was preferred. Comparing regression to latent structures-1 and regression to latent structures-2 it should be noted that the second can be used in the correlation between the response matrix values y but in this case the advantage is not used. Thus regression method to latent structures was selected-1. After it is possible to define a matrix of containing factors to convert, by means of which the coordinates points in the test space PC products can be judged on the numerical values of substandard products abnormalities.

To confirm the efficiency of the method will conduct experimental studies it is necessary to choose a training and a test sample. The training set is built on the basis of the 46 characteristics of a variety of process deviations. Table 5 shows the parameters deviations proportional electromagnetic drive used for training and in Table 6 are used for verification. Table 7 shows that learning is used

Table 6: The parameters of proportional electromagnets used for testing

No. of DCM	The number of turns of the winding (%) of nominal	Saturation magnetic induction armature material (%) of nominal	Saturation induction of the Yoke (%) of the nominal value	Saturation induction magnetic body material (%) of nominal
43	100	120	90	100
44	100	100	90	120
45	100	120	100	90
46	100	100	120	90

Table 7: Dependence described dispersion of the number of used PC

Number of PC	Describes the dispersion (%)
1	99.61832
2	99.73971
3	99.95560
4	99.99284
5	99.99686
6	99.99800
7	99.99934
8	99.99964
9	99.99978
10	99.99995
11	99.99997
12	100.00000

as DCM to “clean” the defects and multiple defects immediately. After the selection of the training sample DCM, you must convert them into the space of the PC. Table 7 shows the dispersion described on the number of used PC. The table shows that for this experiment is sufficient to use only one of the PC. From Table 7 shows that for calibration of only one missing application PC. However, the check in this example the error associated with retraining. To do this we carry out the calibration with the use of 1-2 and three of the PC and determine the error. Determination of error obtaining the parameters of proportional electromagnets (Table 8 and 9). It is evident that the application of two or three of the PC sets the revaluation and increases accuracy. For one PC parameters were determined with an error not exceeding 3%.

The analysis of existing methods of classification. In this case the classification is a procedure in which the objects are divided into groups (classes) in accordance with the numerical values of the variables characterizing the properties of these objects (Rasouli and Ghavami, 2016). To select the method of the following requirements have been put forward:

- Ability to work with a large array of data source as in this case an array of data can be of great dimension
- Ability to set the level of errors of the first and second kind, since they are an important parameter for evaluating the quality of the manufacturing process
- The result should not depend on the chosen form of the distribution to avoid more mistakes
- It is desirable that the method of working with a minimum number of samples in the training set to simplify and reduce the time spent

Table 8: Error matrices for one, two or three participating PC

Parameter No. of PC/DCM	The number of turns of the winding (%) of nominal			Saturation magnetic induction armature material (%) of nominal		
	1	2	3	1	2	3
43	0.03	4.31	6.87	0.71	11.73	16.45
44	1.53	4.06	2.33	2.53	4.28	7.53
45	0.04	1.85	7.09	0.70	12.12	15.90
46	1.64	2.93	2.03	2.65	3.49	6.01
Max. error	164	4310	7.09	2.65	12.12	16.45

Table 9: Error matrices saturation induction

Parameter No. of PC/DCM	Saturation induction of the magnetic material Yoke (%) value			Saturation magnetic magnetic body material (%) of nominal		
	1	2	3	1	2	3
43	0.11	9.24	11.33	0.10	8.04	9.81
44	1.71	2.78	3.97	1.28	2.06	2.90
45	0.11	8.58	10.08	0.12	9.22	10.79
46	1.37	1.76	2.46	1.84	2.34	3.21
Max. error	1.71	9.24	11.33	1.84	9.22	10.79

- The method should be sensitive to outliers and should allow their definitions
- It is desirable that the result does not depend on the number of PC to reduce their number to a minimum
- The method should allow most easily separate the raw data into clusters

Given the fact that in order to control the process of production is important to have the ability to set the level of errors of the first and second kind the most urgent to solve the problem is formally independent modeling of class analogies. To illustrate the method of classification as the original data used training sample of dynamic characteristics of proportional electromagnetic actuators with various defects. For the experiment were used for seventeen DCM with spring defects, reduced the initial gap blockage anchor surface and a group of seventeen DCM without defects. The test sample is included in one of the defective characteristics. Figure 9 shows the form of the test characteristics. In each of the study characteristics were determined by approximation and was taken in 1500 current values at fixed values of the magnetic flux. Further, the matrix current values at fixed values of the magnetic flux transformed into the space of the principal components (Fig. 10). We use the value of the first two of the PC as they describe the 99.91% of the total variance.

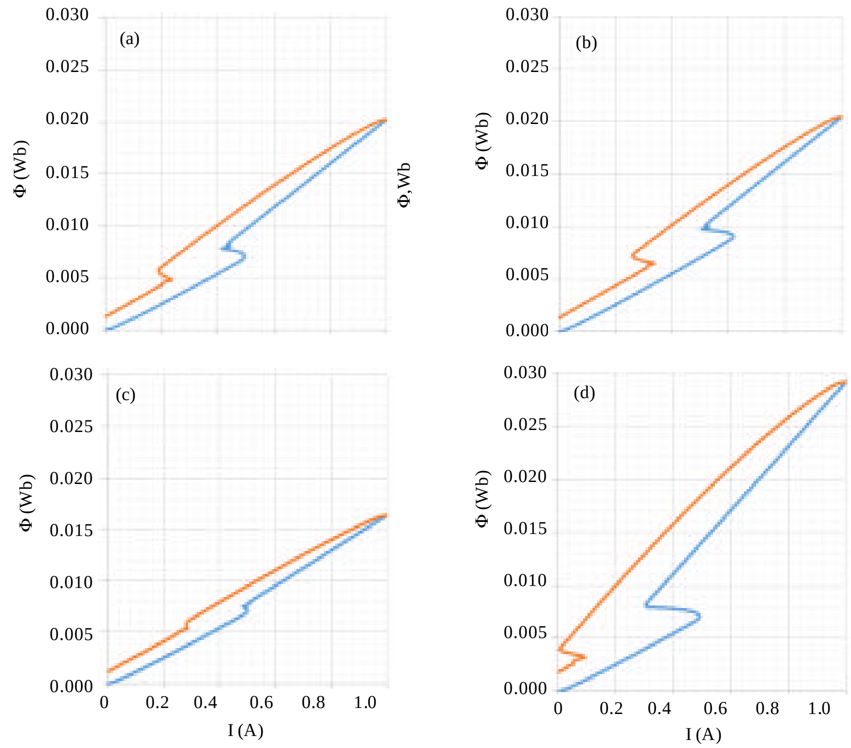

Fig. 9: Forms DCM under study defects of proportional electromagnets

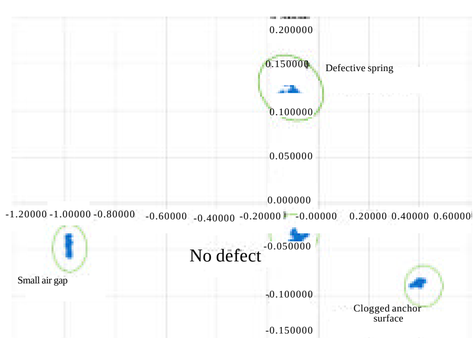

Fig. 10: The dynamic characteristics of the magnetization in the space of two principal components

CONCLUSION

To separate the training sample into groups and classification DCM of the test sample was used method of formal independent modeling of class analogies. Test assumptions about belonging elements test sample to each of the groups. As a result, each test sample was DCM correctly assigned to their group.

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