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# MULTIVARIATE STATISTICAL INVESTIGATION OF CARBON CONSUMPTION FOR HSS REDUCTION CELL

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## Abstract

In the aluminium reduction technology there is no full awareness concerning the dependence of technical-economic indices (TEI) including anode paste (AP) consumption on the changes of raw materials properties and technology parameters. Availability of this information could improve the effectiveness of the reduction technology control.

In the paper the multivariate statistical treatment of anode paste consumption depending on the electrolysis parameters is applied. Using principal component analysis the parameters which greatly influence on the anode paste consumption are determined.

Statistical models for paste consumption for single potroom and for comparison of the results between rooms are received. Anode paste consumptions if the parameters changed by three Standard deviations are calculated.

## Introduction

Variation of technical-economic indices (TEI) in aluminum production process, anode paste consumption including, with changing raw material and technology is poorly known. Information about dependence of technical-economic indices on individual process variables is available in odd bits only. Complex dependencies of TEI on raw materials parameters and technology would certainly improve efficiency of aluminum production control.

The simplest and most attractive method to produce such dependences is the multiple regression derived from sample data [1]. However application of classical regression analysis is obstructed by colligation, correlatedness of many process variables (multicollinearity). Multicollinearity of data makes the matrix columns closer to the linear-dependent and, hence, the data matrix determinant tends to zero. Under these conditions the least square method (LSM) used to find the regression coefficients yields wrong results because it divides by this determinant.

Methods of overcoming the multicollinearity are different, e.g. to improve the least square method [1], to delete interrelated data from analysis; however, we think that most universal and mathematically sound is to process these data by the method of principal components [2, 3, 4].

The principal component method to analyze dependences of the systems of random variables $x_1, \ldots x_r$ is based on linear transformation:

$$\begin{aligned} x_1 &= l_{11}PC_1 + \ldots + l_{1r}PC_{\hat{e}}; \\ &\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ x_r &= l_{r1}PC_1 + \ldots + l_{rr}PC_{\hat{e}}, \end{aligned} \qquad (1)$$

or in the matrix form

$$\vec{X} = L \cdot \overrightarrow{PC}, \qquad (2)$$

where $\vec{X} = \begin{pmatrix} x_1 \\ \vdots \\ x_r \end{pmatrix}$; $\overrightarrow{PC} = \begin{pmatrix} PC_1 \\ \vdots \\ PC_r \end{pmatrix}$ is the column vector; $L = \left\| l_{ij} \right\|$ is the square matrix sizing $r \times r$; $PC_1, \ldots PC_r$ are the uncorrelated (orthogonal) normalized new variables. It is these variables that are called the principal components.

To present the initial random variables in form (1) has several advantages. Variance of each random value $x_i$: $D[x_i] = l_{i1}^2 + \ldots + l_{ir}^2$, $i = \overline{1,r}$; therefore, value $l^2_{ij}$ can be called contribution of $PC_i$ component into variance of variable $x_i$, and $l_{1j}^2 + \ldots + l_{rj}^2 -$ contribution of $PC_j$ component into the total variance of all variables. The first principal component $PC_1$ of variables $x_1, \ldots x_r$ is the normalized linear combination of these variables, exhibiting maximum variance. The second principal component $PC_2$ is the normalized linear combination $x_1, \ldots x_r$, exhibiting maximum variance under condition of uncorrelatedness with $PC_1$. $PC_3$ is the normalized linear combination $x_1, \ldots x_r$ under condition of uncorrelatedness with $PC_1$ and $PC_2$.

Practical studies, where the initial variables under consideration are numerous, tend to isolate a small number of principal components with big variances, while other principal components are discarded to «contract» the space. The method of principal components was proposed in 1901 by Pearson to be later detailed by Hotelling (1933).

Transformation (1) and the principal components are sought as follows:

Let covariance matrix of the system of random variables $x_1, \ldots x_r$ be known. If variables $x_1, \ldots x_r$ are centered and normalized the covariance matrix is equal to correlation matrix Q and then is considered in the analysis. In [1, 2] the system of uncorrelated components $PC_1, \ldots PC_r$ is proved to be obtained on the basis of eigenvectors $\vec{u}_j$ of matrix Q, taken in decreasing order of respective eigenvalues $\lambda_j$. $\lambda_1 > \lambda_2 > \ldots > \lambda_r$.

$$\overrightarrow{PC}_j = \frac{1}{\sqrt{\lambda_j}} \vec{u}_j^T \vec{x} \qquad (3)$$

or in matrix formulation

$$\overrightarrow{PC} = \Lambda^{-\frac{1}{2}} U^T \vec{X}, \qquad (4)$$

where $\Lambda$ is the diagonal matrix of eigenvalues, U is the matrix made of eigenvectors.

Expressing vector $\vec{X}$ from (4) have

$$\vec{X} = U\Lambda^{\frac{1}{2}}\overrightarrow{PC} \tag{5}$$

Equating (5) and (2) have $L = U\Lambda^{\frac{1}{2}}$ and columns of coefficients for PC in system (1) are

$$\vec{l}_k = \sqrt{\lambda_k} \cdot \vec{u}_k .$$

When the system of principal components (4) is produced researchers use different methods depending on the purpose:

1. consider location of initial parameters of $x_1, \ldots x_r$ in the new coordinate system $PC_1, \ldots PC_r$ in compliance with system (1);
2. consider the first principal components – generally they carry the sense load of a part of initial parameters because they combine correlated initial parameters into groups;
3. consider radii of initial parameters and radii of measurement points in the PC system to divide parameters and measurement points into clusters;
4. set up a linear regression of the technical-economic index of interest in new orthogonal PC of variables

   $$Y_{TEI} = a_1PC_1 + a_2PC_2 + \ldots + a_rPC_r, \tag{6}$$

   frequently the latest least significant $PC_s, \ldots PC_r$ can, at this, be discarded;
5. given a clear-cut conceptual physical treatment of the principal components it is possible to turn our attention to this equation (6), to produce the dependence of $Y_{TEI}$ index of our interest on isolated PC directions.

However, in most cases it is desirable to derive dependence of TEI indices on initial process variables; this can be achieved by substitution of (4) into (6).

## Sample Data

Nadvoitsy Aluminium Smelter comprises 4 potrooms: 3 potrooms – with horizontal stud Soderberg (HSS) cells and 1 potroom with prebaked anode cells. Anode paste consumption was analyzed in the first two potrooms (potroom №1 and potroom №2). During the period under consideration these potrooms used anode paste from single supplier; this makes possible to trace the properties of the paste by manufacturer's certificates. The sample data contained monthly average data from March 2009 to October 2010 (20 observations) and 20 variables (18 basic and 2 TEI, Table 1).

Noise level in the monthly average parameter values is lower than in the daily average or weekly average values. Tessier et al. in [5] also notes expedience of using in statistical analysis of monthly average indices instead of daily average or weekly average. The variables were selected on the basis of works [6-8].

## Analysis

Multivariate statistical analysis was carried out with Statistica and MS Excel software. 10 PCs explain as much as 95.76 % of variance of initial data for potroom №1 and 96.04 % of total variance for potroom №2, meanwhile 18 PCs explain the entire variance of initial data.

Table 1. Parameters included into sampling for analysis of anode paste consumption

| Parameter type | Parameter | Identification code |
|---|---|---|
| Basic | AP ash content; | As |
| | AP sulfur content; | S |
| | devolatilization; | Vol |
| | AP softening point; | Ts |
| | bath temperature; | BT |
| | bath depth; | BL |
| | anode height; | h$_a$ |
| | AP flowability; | Cf |
| | AP apparent density; | Da |
| | AP real density; | Dr |
| | AP mechanical strength; | Ms |
| | AP porosity; | P |
| | AP total reactivity; | CO$_2$_dest |
| | AP oxidation; | CO$_2$_oxid |
| | AP dust loss; | CO$_2$_dust |
| | AP specific electric resistance (SER); | R |
| | anode current density; | CDa |
| | specific dust yield; | Dust |
| Accessory* | Current efficiency; | CE |
| | AP consumption. | CC |

*Accessory parameters do not take part in calculation of coefficients for conversion to PC, but are reflected in the principal component plane to analyze the nature of dependencies.

Tables 2 and 3 show contributions of parameters into the first 5 PCs. It is common to consider contribution into the first PCs, as they describe more than a half of changes in the initial parameters (in our case 5 PCs describe ~75-76 % of data variance).

Table 2. Contribution of variables into the first 5 PCs for potroom №1

| Parameter | PC1 | PC2 | PC3 | PC4 | PC5 |
|---|---|---|---|---|---|
| SER | 0,032 | **0,131** | 0,001 | 0,050 | 0,003 |
| Mechanical strength | 0,006 | 0,012 | **0,166** | **0,104** | 0,013 |
| Porosity | **0,145** | 0,001 | 0,048 | 0,043 | 0,012 |
| Sulfur | 0,000 | 0,001 | **0,169** | 0,001 | 0,086 |
| Total reactivity | 0,047 | 0,063 | **0,169** | 0,010 | 0,037 |
| Oxidation | 0,015 | 0,098 | **0,138** | 0,016 | 0,000 |
| Dust loss | 0,063 | 0,018 | **0,108** | 0,072 | 0,061 |
| Apparent density | 0,085 | 0,068 | 0,016 | 0,097 | 0,022 |
| Real density | 0,001 | **0,142** | 0,036 | 0,030 | 0,089 |
| Dust yield | 0,004 | 0,050 | 0,014 | 0,026 | **0,439** |
| Softening point | 0,013 | **0,181** | 0,019 | 0,032 | 0,007 |
| Flowability | 0,085 | 0,014 | 0,001 | **0,142** | 0,046 |
| Ash content | 0,008 | **0,135** | 0,005 | 0,075 | 0,088 |
| Specific dust yield | 0,085 | 0,001 | 0,021 | **0,174** | 0,040 |
| Anode current density | **0,119** | 0,009 | 0,001 | 0,052 | 0,013 |
| Bath temperature | **0,149** | 0,004 | 0,002 | 0,015 | 0,009 |
| Bath level | 0,031 | 0,062 | 0,043 | 0,014 | 0,028 |
| Anode height | **0,112** | 0,011 | 0,043 | 0,047 | 0,006 |

For both potrooms the first direction (PC1) is specified by contribution of the following parameters: porosity, anode current density and bath temperature. In the first potroom big contribution into PC1 is made by the anode height, in the second – by dust loss.

The second direction (PC2) is specified by the following parameters which made a big contribution: SER, real density, softening point and ash content, this is observed in both potrooms.

In PC3 contribution is made by the following variables: mechanical strength, sulfur content in the anode paste, total reactivity and oxidation. In addition to these variables, big contribution in the first potroom is made by the dust loss.

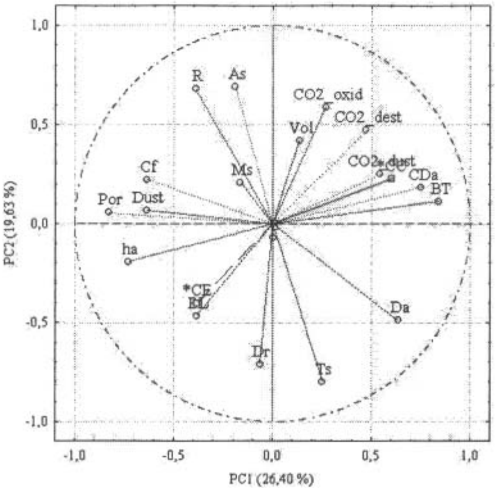
In both potrooms PC4 is specified by dust yield.

Table 3. Contribution of variables into the first 5 PCs for potroom №2

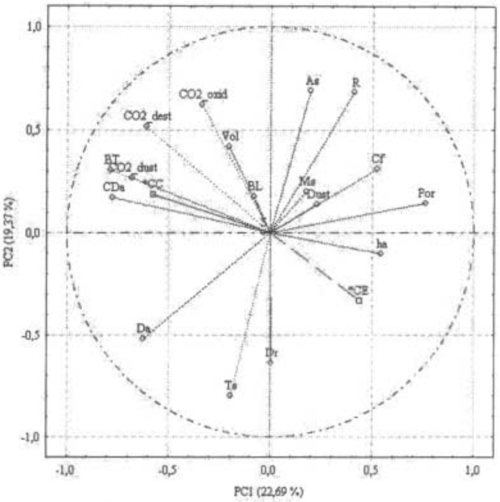
| Parameter | PC1 | PC2 | PC3 | PC4 | PC5 |
|---|---|---|---|---|---|
| SER | 0,041 | **0,132** | 0,004 | 0,054 | 0,001 |
| Mechanical strength | 0,008 | 0,012 | **0,212** | 0,002 | 0,075 |
| Porosity | **0,143** | 0,006 | 0,082 | 0,030 | 0,011 |
| Sulfur | 0,000 | 0,000 | **0,184** | 0,067 | 0,003 |
| Total reactivity | 0,091 | 0,076 | **0,112** | 0,000 | 0,004 |
| Oxidation | 0,028 | **0,111** | **0,113** | 0,002 | 0,015 |
| Dust loss | **0,113** | 0,021 | 0,060 | 0,005 | 0,021 |
| Apparent density | 0,096 | 0,078 | 0,029 | 0,008 | 0,052 |
| Real density | 0,000 | **0,117** | 0,048 | 0,000 | **0,189** |
| Dust yield | 0,010 | 0,051 | 0,019 | **0,175** | 0,038 |
| Softening point | 0,009 | **0,183** | 0,037 | 0,000 | 0,008 |
| Flowability | 0,067 | 0,028 | 0,003 | 0,048 | **0,164** |
| Ash content | 0,009 | **0,135** | 0,016 | 0,089 | 0,003 |
| Specific dust yield | 0,013 | 0,006 | 0,002 | **0,419** | 0,012 |
| Anode current density | **0,147** | 0,008 | 0,016 | 0,062 | 0,002 |
| Bath temperature | **0,151** | 0,026 | 0,009 | 0,000 | 0,055 |
| Bath level | 0,002 | 0,009 | 0,001 | 0,001 | **0,263** |
| Anode height | 0,073 | 0,003 | 0,053 | 0,037 | 0,084 |

Thus, in independent analysis in different potrooms the first principal components had similar sense load.

Of great interest are produced in the course of analysis projections of variables in PC planes (Figures 1 and 2) which make possible to define the nature of dependencies between the parameters. PC planes are space cuts – (projections) of multidimensional space. According to the rules of method [9], variable projections are interpreted as follows: directly proportional between themselves are the variables in one square, inversely proportional are the variables in opposite squares. Nothing can be said about dependencies between the variables in the neighboring squares.



□ – auxiliary variables (CC and CE)
Figure 1. Variable projections in plane PC1 and PC2 for potroom №1



□ – auxiliary variables (CC and CE)
Figure 2. Variable projections in plane PC1 and PC2 for potroom №2

Analysis of variable projections in PC by Figure 1 and Figure 2 shows that consumption of anode paste is the more the more are the values of total reactivity, oxidation, dust loss, bath temperature, devolatilization and anode current density, and the less are the current efficiency, real density of anode paste, anode height and bath level.

Then a PCA model is constructed where AP consumption acts as the sought for function and PC values in time – as the arguments of the sought for multiple regression equation. We should note that on PC it is possible to construct an ordinary classical regression, because the principal components are independent between themselves. Equations (7) and (8) are PCA models for potroom №1 and potroom №2, respectively.

$$\begin{aligned} CC1 = 502.71 + 13.5 \cdot PC1 + 5.07 \cdot PC2 + 0.04 \cdot PC3 + \\ 8.28 \cdot PC4 - 2.02 \cdot PC5 + 6.19 \cdot PC6 - \\ 5.44 \cdot PC7 + 3.98 \cdot PC8 + 4.81 \cdot PC9 + 1.77 \cdot PC10 - \\ 4.42 \cdot PC11 + 3.02 \cdot PC12 - 1.03 \cdot PC13 + \\ 5.73 \cdot PC14 - 2.77 \cdot PC15 + 0.26 \cdot PC16; \end{aligned} \tag{7}$$

$$\begin{aligned} CC2 = 500.47 - 11.42 \cdot PC1 + 3.72 \cdot PC2 - 3.09 \cdot PC3 \\ + 2.09 \cdot PC4 + 0.34 \cdot PC5 - 3.36 \cdot PC6 - \\ 7.26 \cdot PC7 - 4.58 \cdot PC8 - 7.28 \cdot PC9 + 0.84 \cdot PC10 - \\ 6.92 \cdot PC11 - 0.13 \cdot PC12 - 4.36 \cdot PC13 + \\ 2.05 \cdot PC14 - 3.77 \cdot PC15 - 1.18 \cdot PC16, \end{aligned} \tag{8}$$

where $CC1$ and $CC2$ are AP consumption for potroom №1 and potroom №2, respectively;

$PC1 \ldots PC16$ are the principal components acting as regressors in the PCA model.

Both PCA models describe well the AP consumption, the coefficient of determination of regression equation (7) $R^2=0.923$, of equation (8) $R^2=0.978$. Fisher's ratio test showed that the models can be used for prediction ($F>F_{cr}$ in both cases).

Equations (7) and (8) are inconvenient for practical use, even though they make possible to model AP consumption depending on the initial indices, and also make possible to see the effect of an individual PC on AP consumption.

To compare the effect of initial parameters on AP consumption we pass to equation in centered variables by formulas (4) and (6).

$$\begin{aligned} CC1 = 502.71 + 0.91\cdot R - 5.65\cdot Ms - 3.25\cdot P - 7.14\cdot S + \\ 2.51\cdot CO_2\_dest + 1.69\cdot CO_2\_oxid + 5.24\cdot CO_2\_dust + \\ 4.13\cdot D_r - 5.82\cdot Vol - 5.93\cdot Ts + 9.86\cdot As + \\ 5.77\cdot Dust - 8.58\cdot CD_a + 5.94\cdot BT + 4.53\cdot BL - 15.01\cdot h_a; \end{aligned} \quad (9)$$

$$\begin{aligned} CC2 = 500.47 + 2.35\cdot R - 11.28\cdot Ms - 2.2\cdot P - 8.28\cdot S + \\ 0.08\cdot CO_2\_dest - 2.17\cdot CO_2\_oxid + 6.07\cdot CO_2\_dust + \\ 4.67\cdot D_r - 10.94\cdot Vol - 6.34\cdot Ts + 10.22\cdot As + \\ 0.53\cdot Dust - 8.84\cdot CD_a + 8.09\cdot BT + 5.69\cdot BL - 13.39\cdot h_a, \end{aligned} \quad (10)$$

where $CC1$ and $CC2$ are the AP consumption for potroom №1 and potroom №2, respectively; denotations of variables are given in Table 1. One can see that similar parameters of the anode paste and the process have similar signs in equations for different potrooms which is indicative of consistency of the study.

The models produced made possible to construct plots on the same plane with real AP consumption (Figures 5 and 6). Good coincidence of real and predicted AP consumption is apparent, respective approximation coefficients are shown in Figure 7 and Figure 8.

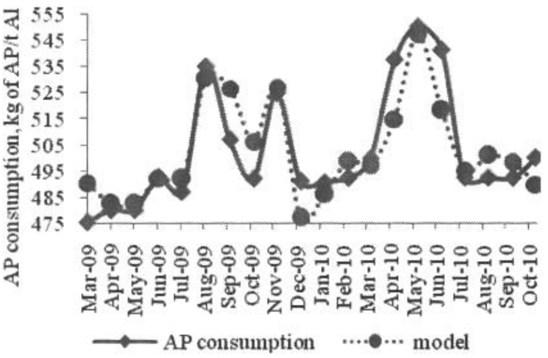


Figure 5. Comparison of AP consumption and modeled consumption for potroom №1

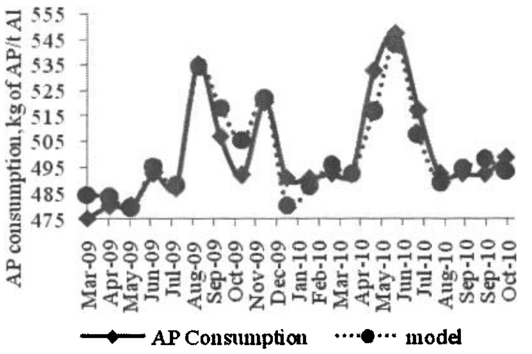


Figure 6. Comparison of AP consumption and modeled consumption for potroom №2

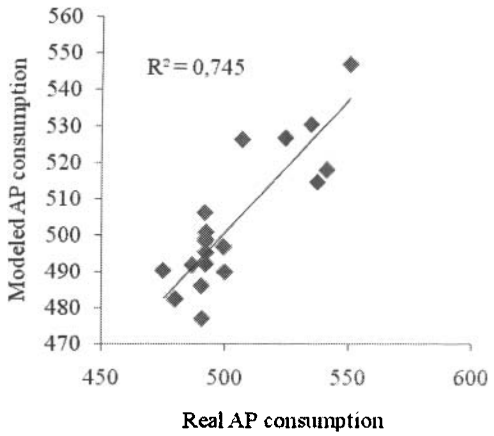


Figure 7. Modeled AP consumption vs. real for potroom №1

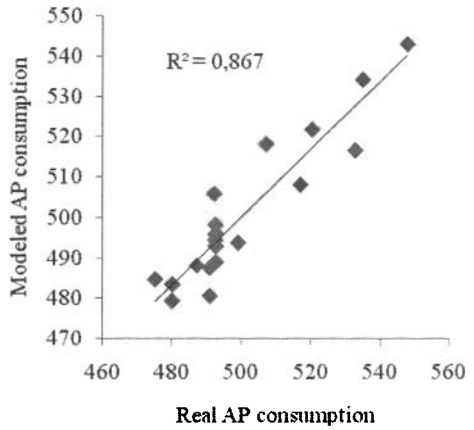


Figure 8. Modeled AP consumption vs. real for potroom №2

Transforming the centered parameters into real ones we have effect of each individual parameter on AP consumption (Table 4). The table shows how decrease of each parameter by 3 values of its standard deviation affects AP consumption in compliance with equations 9 and 10 for different potrooms. E.g. decrease of mechanical strength by 15.7 kg/cm$^2$ increases paste consumption by 16.9 kg by the data of the first potroom and by 33.8 kg by the data of the second potroom. Decrease of bath temperature by 7 degrees decreases AP consumption by 17.8 by the data of the first potroom and by 24.3 kg by the data of the second potroom.

From Table 5 it is apparent that the effect of parameters on AP consumption found by our statistical study is in agreement with known literature data. The exception is only the effect of total reactivity and oxidation in $CO_2$ for potroom №2.

Of course, to make precise numerical effect of the parameters considered on anode paste consumption requires a study with bigger sampling.

Table 4. AP consumption vs. analyzed parameters

| Parameter | Units of measurement | potroom №1 | | potroom №2 | | Consumption variation by literature data |
|---|---|---|---|---|---|---|
| | | Decrease of parameters by SDs* | AP consumption change, kg | Decrease of parameters by SDs* | AP consumptio n change, kg | |
| SER | mcOhm·v | 6,026 | -2,716 | 6,026 | -7,065 | ?** |
| Mechanical strength | kg/$cm^2$ | 15,717 | 16,941 | 15,717 | 33,845 | (+)*** |
| Porosity | % | 0,988 | 9,757 | 0,988 | 6,612 | (+\|-)****[6] |
| Sulfur | % | 0,078 | 21,424 | 0,078 | 24,840 | (+\|-)[10] |
| Total reactivity | mg/$cm^2$·h | 5,559 | -7,528 | 5,559 | 0,244 | (-)*****[6, 11] |
| Oxidation | mg/$cm^2$·h | 2,951 | -5,076 | 2,951 | 6,520 | (-)[6, 11] |
| Dust loss | mg/$cm^2$·h | 3,555 | -15,717 | 3,555 | -18,215 | (-)[6, 11] |
| Real density | g/$cm^3$ | 0,025 | -12,396 | 0,025 | -14,020 | (+)[6, 11] |
| Dust yield | % | 3,397 | 17,448 | 3,397 | 32,823 | (-)[12, 11] |
| Softening point | °C | 6,414 | 17,792 | 6,414 | 19,031 | (-)[6] |
| Ash content | % | 0,075 | -29,575 | 0,075 | -30,662 | (-)[12] |
| Specific dust yield | kg/t Al | 16,365 | -17,306 | 17,009 | -1,592 | (-)[6] |
| Anode current density | A/$cm^2$ | 0,015 | 25,735 | 0,015 | 26,509 | (-)[6] |
| Bath temperature | °C | 6,965 | -17,811 | 7,658 | -24,266 | (-)[6] |
| Bath level | cm | 3,048 | -13,579 | 2,573 | -17,077 | (-)[6] |
| Anode height | cm | 11,473 | 45,029 | 10,447 | 40,158 | ? |

* SD – Standard deviation.

** ? – No information is found in literature about effect of the parameter on paste consumption.

*** (+) – AP consumption increases as the parameter value decreases.

**** (+|-) – Literature sources indicate dual effect of the parameter on AP consumption.

***** (-) –AP consumption decreases with parameter value.

## Conclusion

Application of multivariate statistical processing of data has been considered to analyze anode paste consumption depending on the properties and parameters of electrolysis. The principal component method and multiple linear regression were used to model AP consumption in two potrooms of Nadvoitsy Aluminium Smelter. The method of principal components was used to identify parameters with greatest effect on variation of AP consumption over the period under consideration. The plots of parameter projections in PC plane made possible to find the nature of dependence between the parameters. Derived have been:

- PCA-models to predict AP consumption at the potroom level;
- statistical models to compare effect of parameters between themselves;
- variation of AP consumption with decrease of parameters by 3 SDs.

To specify dependences and derive more accurate models for prediction requires bigger array of statistical data and account of additional parameters affecting AP consumption in HSS cells.

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