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PRACTICAL RESULTS OF THE STUDY OF PHOTOPOLYMER EXPOSURE OF PRINTED CIRCUIT BOARD TOPOLOGY

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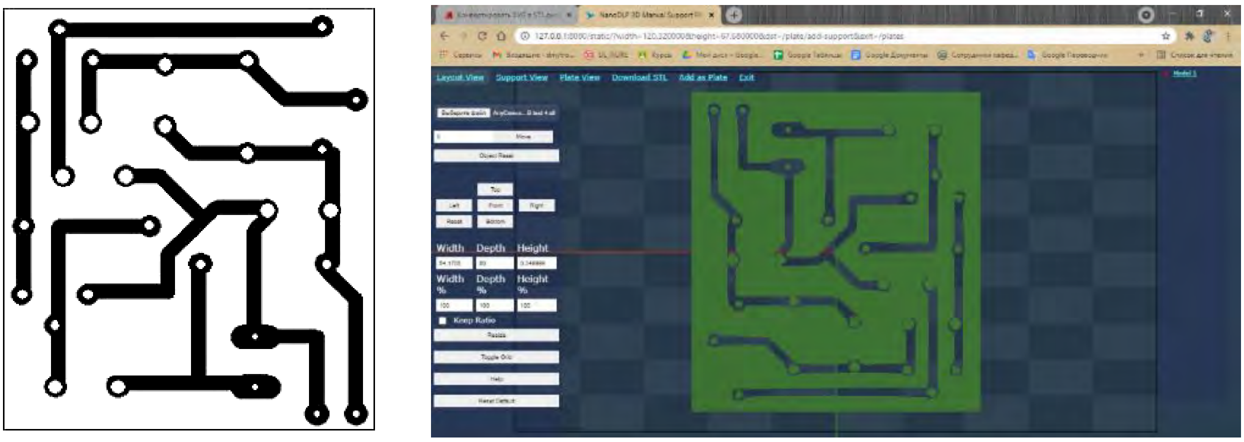
Practical results of studies of deviations of geometric dimensions of the topological structure of printed circuit boards during photopolymer 3D exposure are presented. A series of experiments of topology exposure under different process parameters was carried out. The results of 112 samples were checked using statistical analysis and a regression model of the influence of parameters on the deviation of the geometric dimensions of conductors was built.

Introduction

The modern development of technologies in the field of instrumentation is primarily focused on reducing the size of devices and integrating a large number of modules in one device [1–3]. This leads to the need to reduce the size of both products as a whole and their individual components, assemblies and printed circuit boards. The process of miniaturisation involves not only reducing the size of electronic elements, but also the size of printed circuit boards (PCBs). Photolithography technology is the most suitable for PCB production, but this process is labour-intensive and requires additional costs for creating stencils [4]. The use of stencils limits the flexibility of production, as it takes time to switch to creating new products. In today's automated production environment, this lack of flexibility is a serious limitation. However, one of the possible ways to solve these problems is to develop methods for adapting and optimising the technological parameters of PCB topology exposure using additive 3D printing technologies [5–6]. This topic is relevant because it can solve not only problems with production flexibility but also ensure the required product parameters.

Preparing for the experiment

To conduct the research, a stencil of the PCB topology with dimensions of 80×72 mm was created in the format of a vector image (svg.), which was then converted to a format for 3D printing (stl.) [7–8]. Such an approach to processing and converting a 2D image into a 3D object is necessary to work with the mask in the NanoDLP program, in which it is possible to generate a machine code for sequential execution of commands (G-code) for a DLP/LCD printer, in which the necessary printing parameters will be set, (fig. 1).



a) b)

Fig. 1. Vector image processing for 3D-exponuvannya:
a) vector image; b) 3D-mask

The samples were made using Plexiwire Resin Basic Orange Transparent photopolymer resin, which was chosen because of its high mechanical and technological parameters (short exposure time, minimum possible layer thickness and no harmful effects on personnel), low shrinkage during polymerisation, and high resistance to chemicals, which has a positive effect on the etching process [9–10].

To verify these assumptions, 112 measurements of the deviation of the obtained dimensions from the original geometric ones were carried out. A linear regression model was built taking into account the following parameters:

– resin illumination duration from 7 seconds to 20 seconds;

– radiation intensity maximum 2800 Lm and minimum 1600 Lm;

– emission wavelength 405–435 nm;

– base layer thickness 20 μm and 50 μm.

The created 3D topology of 80×72 mm DP conductors was transferred to foil fiberglass (SF grade DSTU 10316-78) and etched in ferric chloride solution ($FeCl_3$).

In the first experiment, the adhesion of the photopolymer resin to the foil billet was tested. The result confirms the resistance of the photopolymer resin to ferric chloride and high-quality adhesion to the surface, but there is a deviation in the geometric dimensions of the conductor structure by ±0,00847 mm (minimum deviation) with a base conductor size of 2 mm [11–12].

For greater clarity and a better understanding of the influence of parameters on the manufacturing process, the abbreviated results in the range of exposure times from 7 seconds to 11 seconds are shown in table 1.

A graphical description of the dependence of deviations at different parameter values is shown in (fig. 2).

Table 1

Average values of deviations of conductor sizes at different values of parameters in the range from 7 to 11 seconds at different values of exposure parameters

Emission wavelength 405 nm			
Radiation intensity 1600 Lm		Radiation intensity 2800 Lm	
Exposure time, s	Deviation, mm	Exposure time, s	Deviation, mm
7	+0,00847	7	+0,01025
8	+0,01074	8	+0,012925
9	+0,0125	9	+0,0135
10	+0,01375	10	+0,0165
11	+0,01575	11	+0,017
Layer thickness 20 μm		Layer thickness 50 μm	
Exposure time, s	Deviation, mm	Exposure time, s	Deviation, mm
7	+0,0092	7	+0,0102
8	+0,0111	8	+0,01287
9	+0,01225	9	+0,01482
10	+0,0142	10	+0,01625
11	+0,01527	11	+0,018775
Average deviation at 1600 lm radiation intensity and 20 μm layer thickness		Average deviation at 2800 lm radiation intensity and 50 μm layer thickness	
Exposure time, s	Deviation, mm	Exposure time, s	Deviation, mm
7	**+0,008835**	7	**+0,01022**
8	**+0,01092**	8	**+0,01289**
9	**+0,012375**	9	**+0,01416**
10	**+0,013975**	10	**+0,01637**
11	**+0,01551**	11	**+0,01788**

These deviations may be due to the long duration of the photopolymer illumination. This result allowed us to make the following assumptions:

1. There is a linear dependence of the illumination duration on the geometric size of the conductor. The longer the illumination time, the greater the upward deviation of the size, respectively, with a shorter illumination time, the deviation is smaller.

2. At low luminous flux intensity, the photopolymer resin may not be completely polymerised due to the incomplete transparency of the mask screen, which absorbs part of the radiation, which reduces the effect of UV on the resin and shortens the service life of the screen. Thus, the lack of UV radiation can lead to poor

adhesion to the workpiece, resulting in the transfer of the topology to the workpiece leaving the polymer in a semi-polymerised state on the film, which will reduce the service life of the film. Lack of light intensity with poor adhesion of the layer to the workpiece can lead to etching of the conductors and deviation of the dimensions downward from the original.

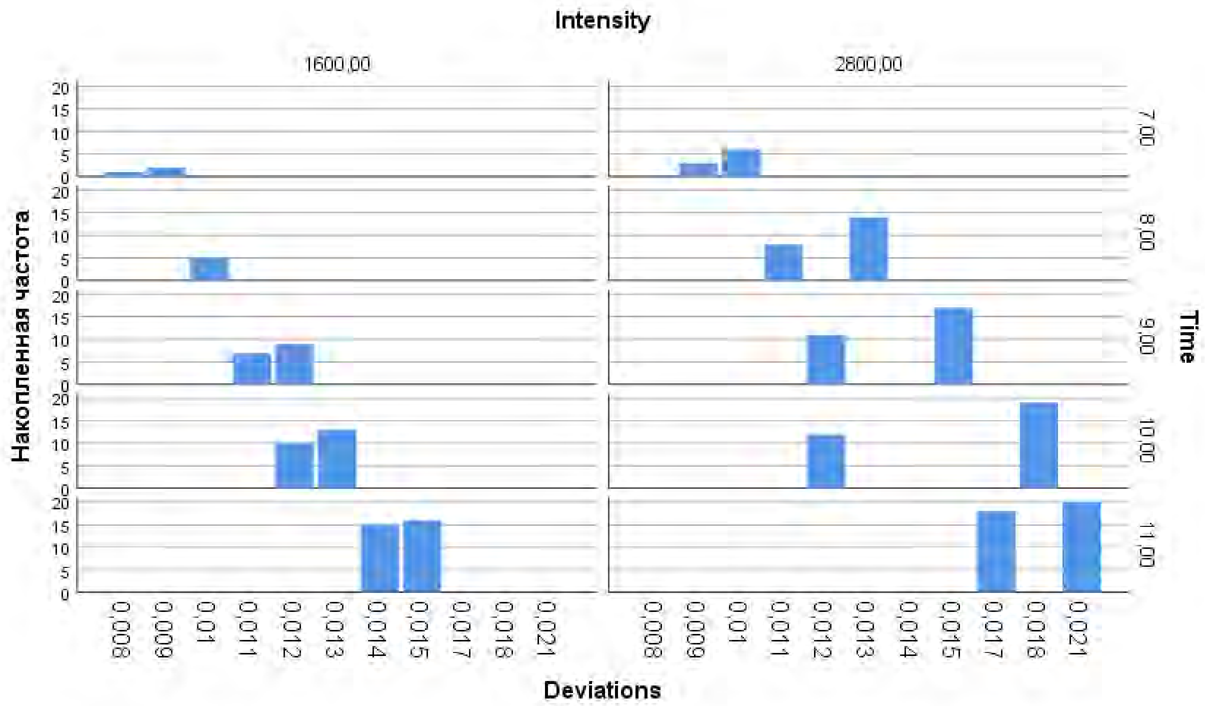


Fig. 2. Dependence of conductor size deviations on exposure parameters

3. The greater the height of the base layer of the photopolymer mask, the greater the gap between the screen and the workpiece. This can lead to a greater diffraction of the light flux, respectively, a greater parasitic illumination of the conductors, (fig. 3).

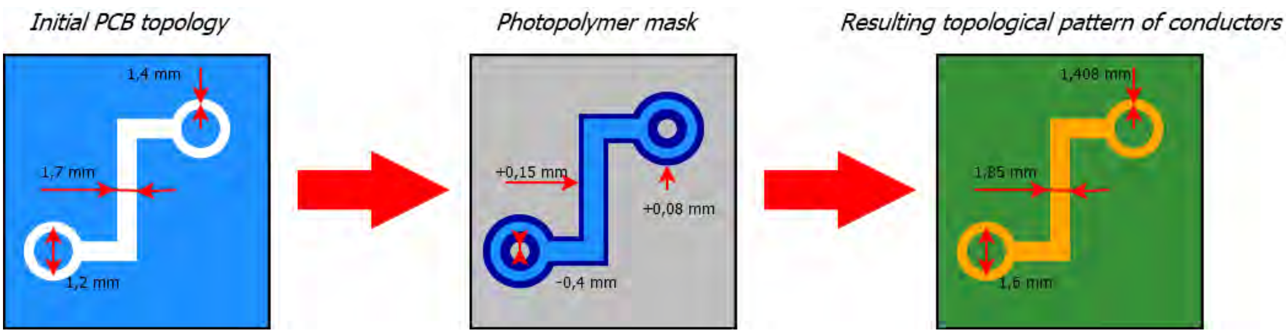


Fig. 3. Schematic representation of deviations in the experiments

A sample of the resulting topology is shown in fig. 4.

a) b) c)

Fig. 4. Production of DS using 3D exposure technology:
a) polymeric photo mask;
b) etching of the DP in ferric chloride solution ($FeCl_3$);
c) finished DP topology

Testing the basic assumptions of multiple linear regression

In order to build a multiple linear regression model, it is necessary to check the underlying assumptions that will confirm or refute the adequacy of the initial values for calculation and make sure that the parameters included in the model really affect the dependent variable.

To check the basic assumptions of multiple linear regression, the following assumptions should be reviewed: no outliers in the measurements; no multicollinearity between the independent variables; normal distribution of residuals; homoscedasticity of the variance of the residuals; linearity of the relationships [13–14].

No measurement errors

All the measurement data in this study are ordinal, so the model passes the first assumption.

This model uses four independent variables (exposure time «Time»; layer thickness «Thickness»; radiation intensity «Intensity»; wavelength «Wavelength»). Based on the rule that the minimum number of measurements for each independent variable is 20, the number of measurements must be at least 100 to build this multiple linear regression. In this case, there are 112 measurements in this model. Therefore, the model passes the second assumption. To check that there are no errors in the measurements, use IBM SPSS Statistics 26. Go to «Analyse»→ «Regression»→ «Linear», enter the model, go to "Statistics" to check for outliers and select «Casewise diagnostics». This will provide some information about the errors. Go to the «Save» button and build additional changes, namely:

– Cook's distance «Cook's»;

– standardised residuals «Residuals»→ «Standardised»;

– standardised predicted values «Predicted Values»→ «Standardised».

The standardised values of these values are necessary to see whether these values are within the normal range. After the settings, we get the table of residual statistics "Residuls Statistics[a]", (fig. 5).

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,0100125	,0255892	,0178008	,00386310	112
Std. Predicted Value	-2,016	2,016	,000	1,000	112
Standard Error of Predicted Value	,000	,000	,000	,000	112
Adjusted Predicted Value	,0101091	,0255967	,0178070	,00386077	112
Residual	-,00328229	,00228059	,00000000	,00107548	112
Std. Residual	-2,996	2,082	,000	,982	112
Stud. Residual	-3,089	2,146	-,003	1,007	112
Deleted Residual	-,00348782	,00242340	-,00000611	,00113094	112
Stud. Deleted Residual	-3,221	2,184	-,005	1,018	112
Mahal. Distance	2,988	5,550	3,964	,884	112
Cook's Distance	,000	,119	,010	,018	112
Centered Leverage Value	,027	,050	,036	,008	112

a. Dependent Variable: Deviations

Fig. 5. Statistics of balances

Based on the fact that the maximum and minimum values of the standardised residuals «Std.Residual» and the standardised predicted values «Std.Predicted Value» do not fall outside the range of ±3. This indicates that there are no outliers in the measurement. «Cook's Distance» is 0,119, which is significantly less than one, which also supports the absence of outliers.

No multicollinearity between independent variables

The next assumption to be tested is the presence of multicollinearity between the independent variables. Go to «Analyse»→ «Regression»→ «Linear», in the «Save» tab, remove the standardised predicted values «Standardised», standardised residuals «Standardised» and Cook's distance «Cook's». Go to the «Statistics» tab, select «Descriptive» statistics and «Collinearity diagnostics». As a result, we get a correlation table, (fig. 6).

Correlations

		Deviations	Time	Thickness	Intensity	Wavelength
Pearson Correlation	Deviations	1,000	,904	,134	,300	,060
	Time	,904	1,000	,000	,000	,000
	Thickness	,134	,000	1,000	,000	,000
	Intensity	,300	,000	,000	1,000	,000
	Wavelength	,060	,000	,000	,000	1,000
Sig. (1-tailed)	Deviations	.	,000	,079	,001	,267
	Time	,000	.	,500	,500	,500
	Thickness	,079	,500	.	,500	,500
	Intensity	,001	,500	,500	.	,500
	Wavelength	,267	,500	,500	,500	.
N	Deviations	112	112	112	112	112
	Time	112	112	112	112	112
	Thickness	112	112	112	112	112
	Intensity	112	112	112	112	112
	Wavelength	112	112	112	112	112

Fig. 6. Correlation of the model

Multicollinearity is a linear dependence between independent variables, i.e. between the predicates themselves (exposure time «Time»; layer thickness «Thickness»; radiation intensity «Intensity»; wavelength «Wavelength»). Between the precursors themselves, the dependence should be incompletely observed in the measurements, or it should be minimal (less than 0,7). In this model, in the «Pearson Correlation», the relationship between the variables «Time», «Thickness», «Intensity» and «Wavelength» is zero. To make sure that there is no multicollinearity, we go to the table of regression coefficients «Coefficients», (fig. 7).

Judging by the variance inflation factor «VIF», which should be less than 5. In this model, the «VIF» between the independent variables is equal to 1, which supports the absence of multicollinearity between the predictors.

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	-,007	,003		-2,225	,028		
	Time	,001	,000	,904	34,847	,000	1,000	1,000
	Thickness	3,575E-5	,000	,134	5,180	,000	1,000	1,000
	Intensity	1,998E-6	,000	,300	11,581	,000	1,000	1,000
	Wavelength	1,584E-5	,000	,060	2,295	,024	1,000	1,000

a. Dependent Variable: Deviations

Fig. 7. Regression coefficients «Coefficients»

The tolerance indicator «Tolerance», which is equal to (1/«VIF»), is a relative indicator of «VIF» and should be greater than 0,2. This is the proportion of variance of the predictor itself, each of the specified predictors, that cannot be obtained from other predictors. In this model, it is complementary to one in all predictors.

In the «Collinearity Diagnostics[a]», when the «Eigenvalues» tend to zero, the «Condition Index» increases, and it should be less than 15, (fig. 8).

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Time	Thickness	Intensity	Wavelength
1	1	4,751	1,000	,00	,00	,01	,00	,00
	2	,136	5,906	,00	,06	,90	,04	,00
	3	,076	7,911	,00	,59	,01	,40	,00
	4	,036	11,465	,01	,34	,09	,55	,01
	5	,001	86,773	,99	,00	,00	,00	,99

a. Dependent Variable: Deviations

Fig. 8. Collinearity Diagnostics «Collinearity Diagnostics[a]»

In this case, in the fifth dimension, this indicator is 86,773, which is a high risk of multicollinearity between predictors. In order to correct this, it is necessary to exclude one variable from the model. Using the «Variance Proportions», we exclude variables with a proportion greater than 0,9. In this case, it is «Wavelength», which is 0,99. We rebuild the model and get (fig. 9).

In the rebuilt model, all the results obtained are consistent with the previous rules. The conditionality index «Condition Index» for all variables is less than 15. Now this model fully meets the assumption of the absence of multicollinearity between independent variables.

Correlations

		Deviations	Time	Thickness	Intensity
Pearson Correlation	Deviations	1,000	,904	,134	,300
	Time	,904	1,000	,000	,000
	Thickness	,134	,000	1,000	,000
	Intensity	,300	,000	,000	1,000
Sig. (1-tailed)	Deviations	.	,000	,079	,001
	Time	,000	.	,500	,500
	Thickness	,079	,500	.	,500
	Intensity	,001	,500	,500	.
N	Deviations	112	112	112	112
	Time	112	112	112	112
	Thickness	112	112	112	112
	Intensity	112	112	112	112

a)

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	7,533E-5	,001		,128	,898		
	Time	,001	,000	,904	34,178	,000	1,000	1,000
	Thickness	3,575E-5	,000	,134	5,081	,000	1,000	1,000
	Intensity	1,998E-6	,000	,300	11,359	,000	1,000	1,000

a. Dependent Variable: Deviations

b)

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Time	Thickness	Intensity
1	1	3,768	1,000	,00	,01	,01	,00
	2	,133	5,314	,01	,09	,86	,05
	3	,076	7,059	,00	,55	,01	,45
	4	,023	12,762	,99	,36	,12	,50

a. Dependent Variable: Deviations

c)

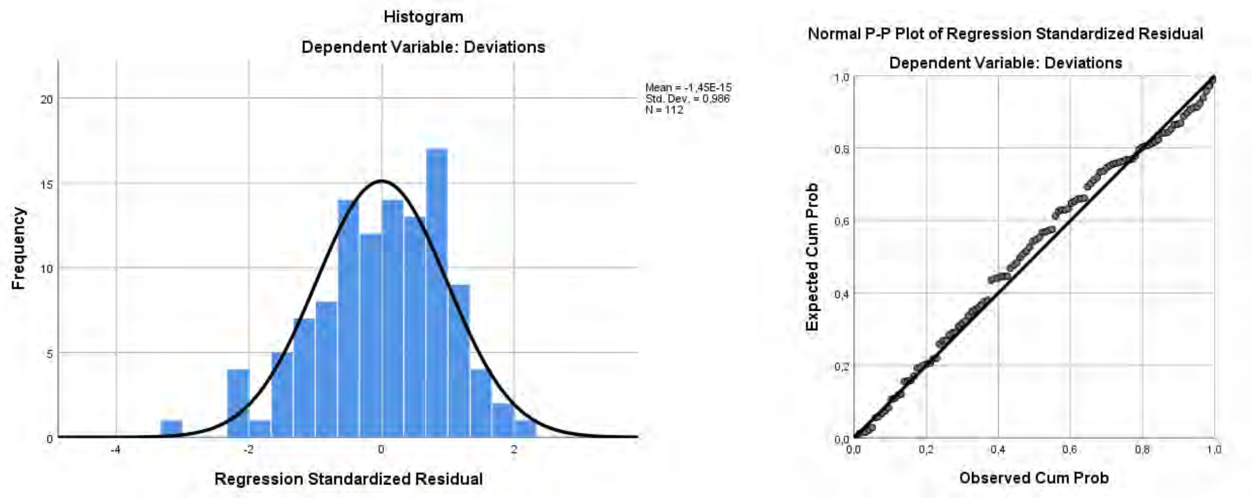
Fig. 9. Results of the above model:
a – model correlations; b – regression coefficients «Coefficientsa»;
c – diagnostics of collinearity «Collinearity Diagnostics[a]»

Normal distribution of residuals

The residual is the difference between the dependent variable and the predicted value of *Y*, through which the regression line passes. To check the normal distribution, you need to draw a distribution graph. Go to the «Analyse»→ «Regression»→ «Linear» masonry. In the «Statistics» tab, deselect «Descriptives» and «Collinearity diagnostics». In the «Plots» tab, select the «Histogram» and «Normal probability plot».

The result is a histogram. Using the histogram, you can see how much the distribution deviates from the theoretical approximation of the Gaussian line, (fig. 10, a).

The plot of the accumulated probabilities shows whether the observations deviate from the theoretical straight diagonal, fig 10, b.



a) b)

Fig. 10. Graphical description of the normality of the residuals distributions: a – histogram of the distribution deviation; b – graph of observations

In order to estimate the deviation of the data from the normal distribution (fig. 10, a) and the deviation of the observations (fig. 10, b), it is necessary to analytically examine these graphs and estimate the distribution of the residuals. In these graphs, you need to estimate the standardised residual, so you need to plot these values separately. Go to «Analyse»→ «Regression»→ «Linear» in the «Save» tab, select to save the standardised residual «Residuals»→ «Standardised» and the unstandardised residual «Residuals»→ «Unstandardised». As a result, in the «Data View» we get additional values RES_1 and ZRE_2, using these values it is possible to check the normality of the values.

Go to the «Descriptive Statistics» analysis, «Explore» analysis, and transfer the changes you have made. In the "Plots" tab, select the graph for the normality criterion «Normality plots with tests». In the table of the normal distribution criterion «Tests of Normality», in the significance indicators «Kolmogorov–Smirnov» and «Shapiro-Wilk», the significance «Sig.» should be greater than 0,05, which confirms the rule of normality of the residuals distribution, (fig. 11).

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,064	112	,200*	,983	112	,153
Standardized Residual	,064	112	,200*	,983	112	,153

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Fig. 11. Table of normal distribution criterion «Tests of Normality»

In this case, the significance of the standardised «Standardised Residuals» and the unstandardised residual «Unstandardised Residuals» by «Kolmogorov–Smirnov» is 0,2, and by «Shapiro–Wilk» is 0,153, which supports the normal distribution of residuals in the model.

If you build an additional histogram of the standardised values «Descriptive Statistics»→ «Explore»→ «Plots»→ «Histogram», you can compare the standardised histogram with the first histogram, then compare the standard deviation «Std.Dev.» and make sure that they are the same, and the normal distribution of residuals is preserved, (fig. 12).

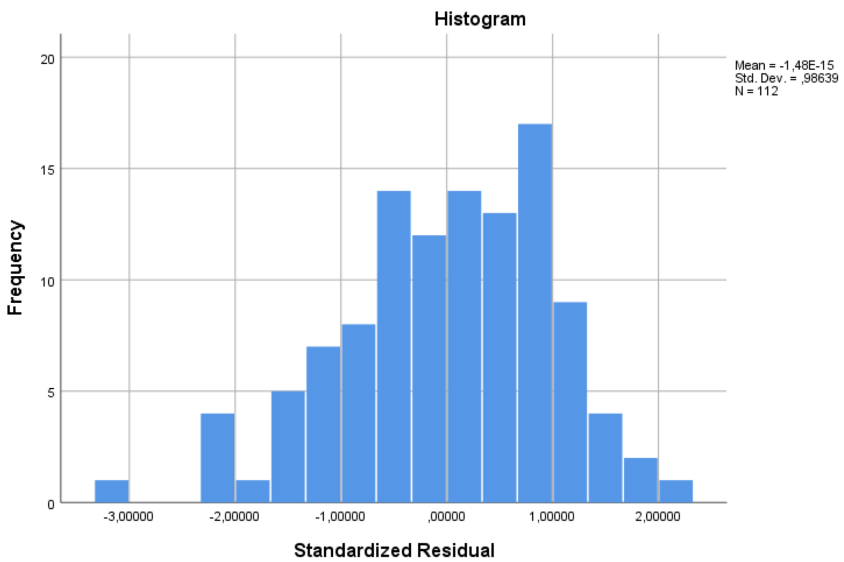


Fig. 12. Standardised balance sheet

Homoscedasticity of the variance of the residuals

Homoskedasticity is the constancy of the variance of the sudden error of a regression model. To test this assumption graphically, go to «Analyse»→ «Regression»→ «Linear»→ «Plots». Select the standardised predicted values (*ZPRED) on the *X*-axis and the standardised residuals (*ZRESID) on the *Y*-axis.

Using the resulting graph (fig. 13), it is possible to view the presence of outliers in the model, whether the values are outside ±3, in this case there are no outliers in the model.

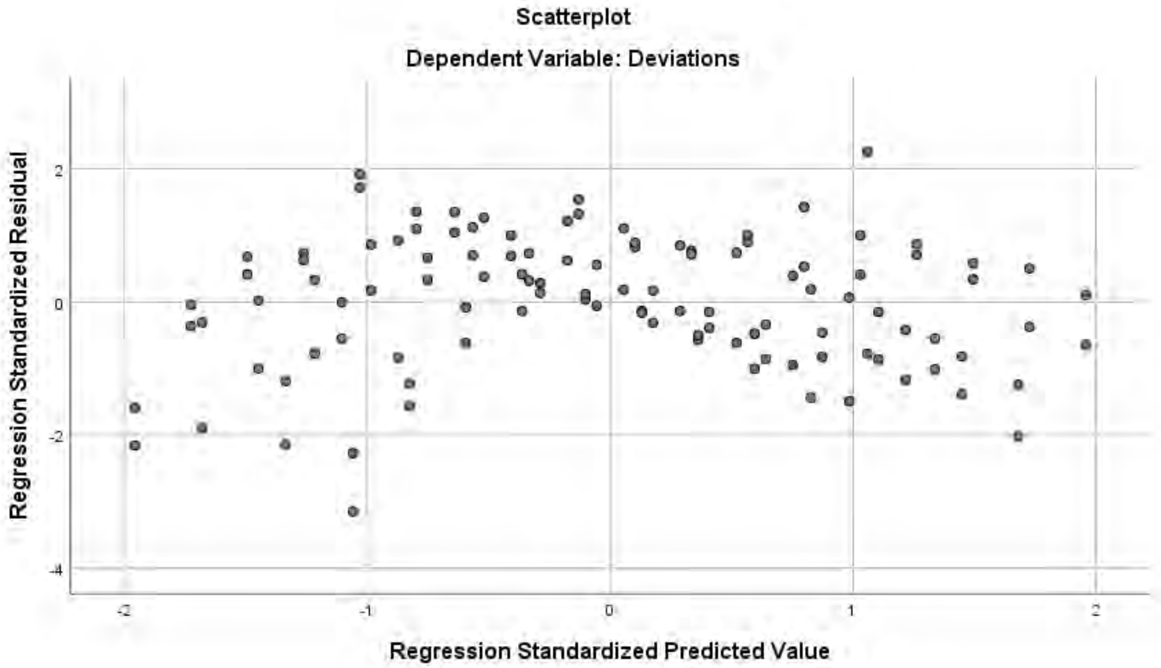
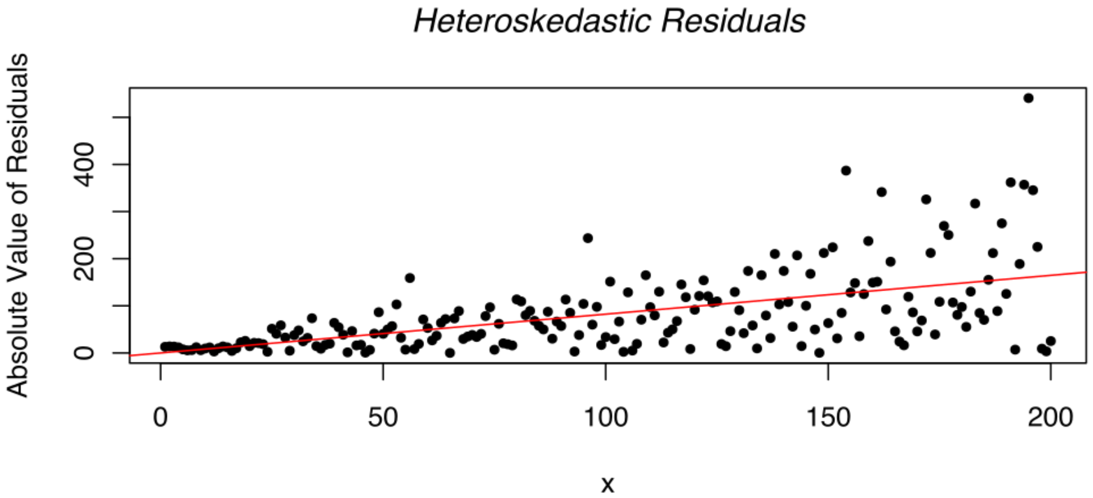


Fig. 13. The resulting homoscedastic distribution

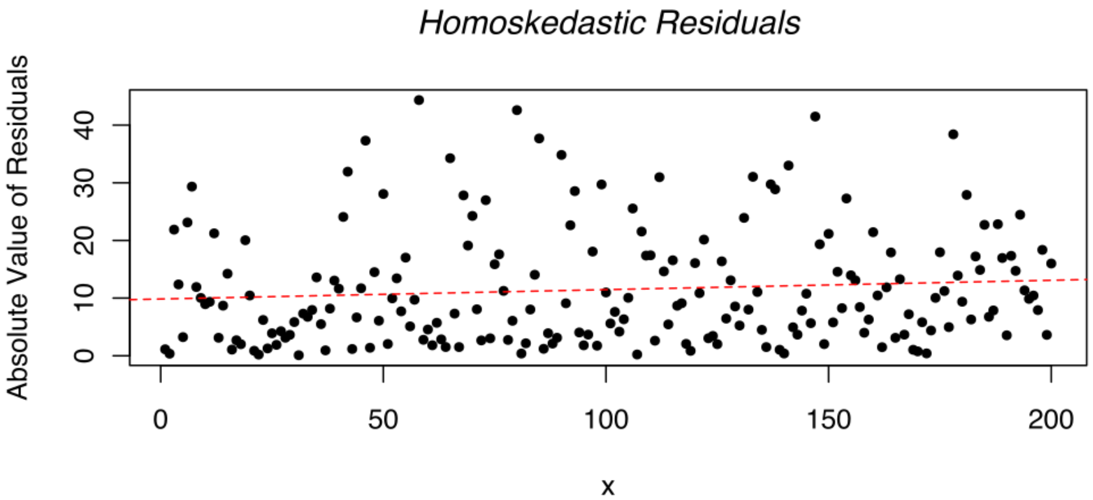
The constancy or not of the variance of errors will be expressed by whether the spread in *Y* is the same with increasing *X*. To explain what homoscedasticity is, let's consider heteroscedasticity, (fig. 14).

Heteroskedasticity (fig. 14, a) is not the constancy of the error variance, it causes the residual distribution to have a regular shape due to the variability of the error variance. The data have a natural shape. If there is a regularity in the shape of the distribution, it is bad for the model, it is necessary that the distribution of values on the *Y*-axis varies randomly. Because when a model is built, the success of the prediction model is not the same over the entire range of values.

The problem with graphically assessing the homoscedasticity of a model is that it is easier to see deviations from heteroscedasticity, but it is difficult to be completely sure that the rules of homoscedasticity of a model are preserved. Therefore, we will use specialised criteria for checking homoscedasticity.



a)

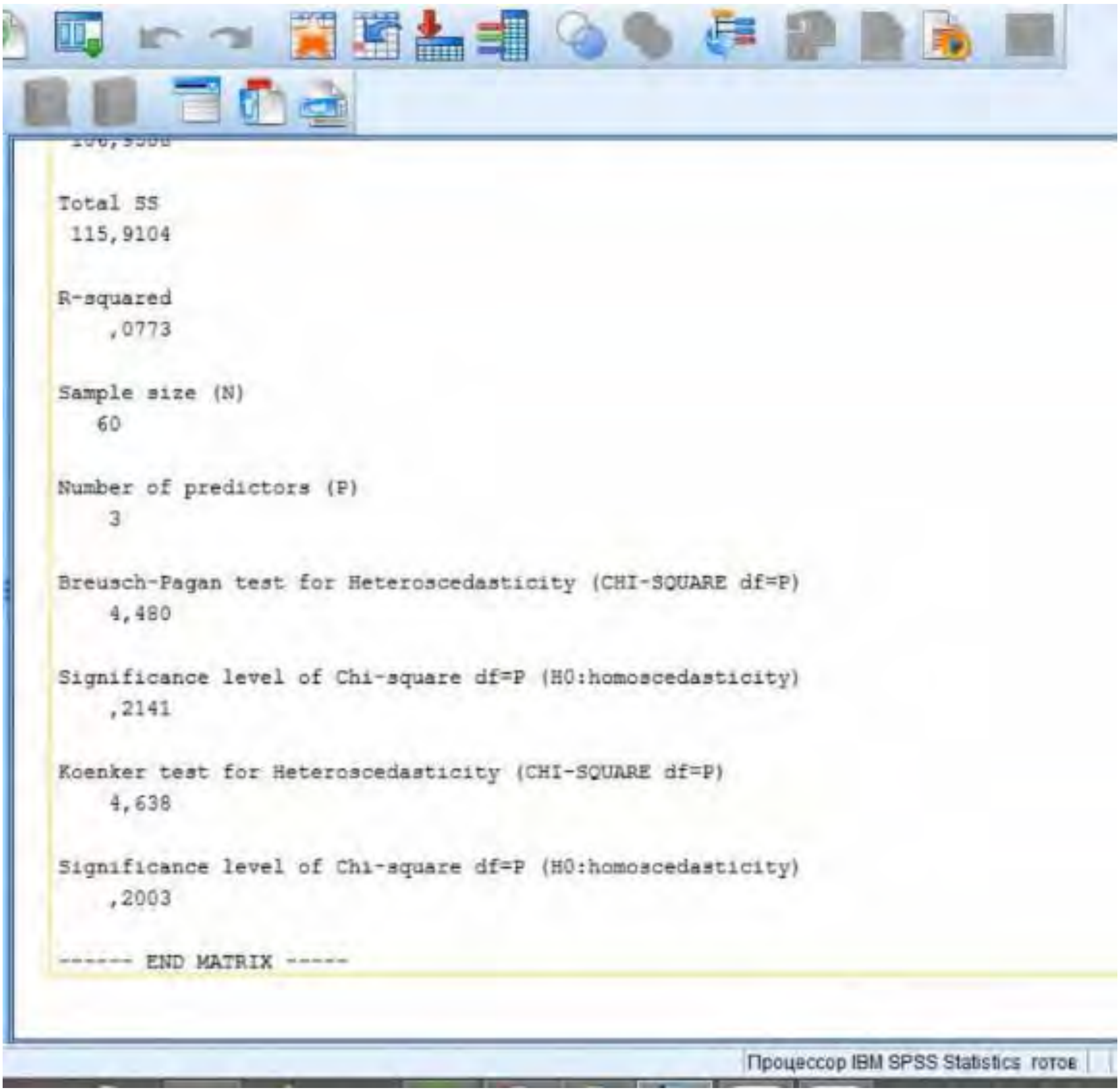


b)

Fig. 14. Homoscedasticity and heteroscedasticity of distributions:
a – example of heteroscedasticity distribution;
b – example of homoscedasticity distribution

To do this, we load additional code into SPSS to check for homoscedasticity. Copy the code, go to «File»→ «New», create a syntax editor «Syntax Editor». In the «BPKTEST» stack, enter the names of the model variables and start building the "Run Selection" calculation.

At the end of the calculation, we look at the «Breush-Pagan» criterion and the «Koenker» criterion. The null hypothesis of these criteria is homoscedasticity. Accordingly, in order to maintain the assumption of multiple linear regression, it is necessary that the values of these criteria are greater than 0,05. In this case, the assumption of homoscedasticity is fulfilled with «Breush-Pagan» equal to 4,480 and «Koenker» equal to 4,638, (fig. 15).



```
Total SS
 115,9104

R-squared
    ,0773

Sample size (N)
   60

Number of predictors (P)
    3

Breusch-Pagan test for Heteroscedasticity (CHI-SQUARE df=P)
    4,480

Significance level of Chi-square df=P (H0:homoscedasticity)
    ,2141

Koenker test for Heteroscedasticity (CHI-SQUARE df=P)
    4,638

Significance level of Chi-square df=P (H0:homoscedasticity)
    ,2003

------ END MATRIX -----
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Fig.15. Mathematical test of homoscedasticity of the model

Linearity of communication

To assess the linearity of the relationships, we use partial regression plots. Go to «Analyse»→ «Regression»→ «Linear»→ «Plots», and check the box to «Produce all partial plots». This function will allow you to get private regression plots for each change, (fig. 16).

Based on the distributions obtained, it is possible to clearly see that there is no nonlinear pattern in the graphs. Therefore, we can conclude that the model meets the requirements of linearity of the relationship.

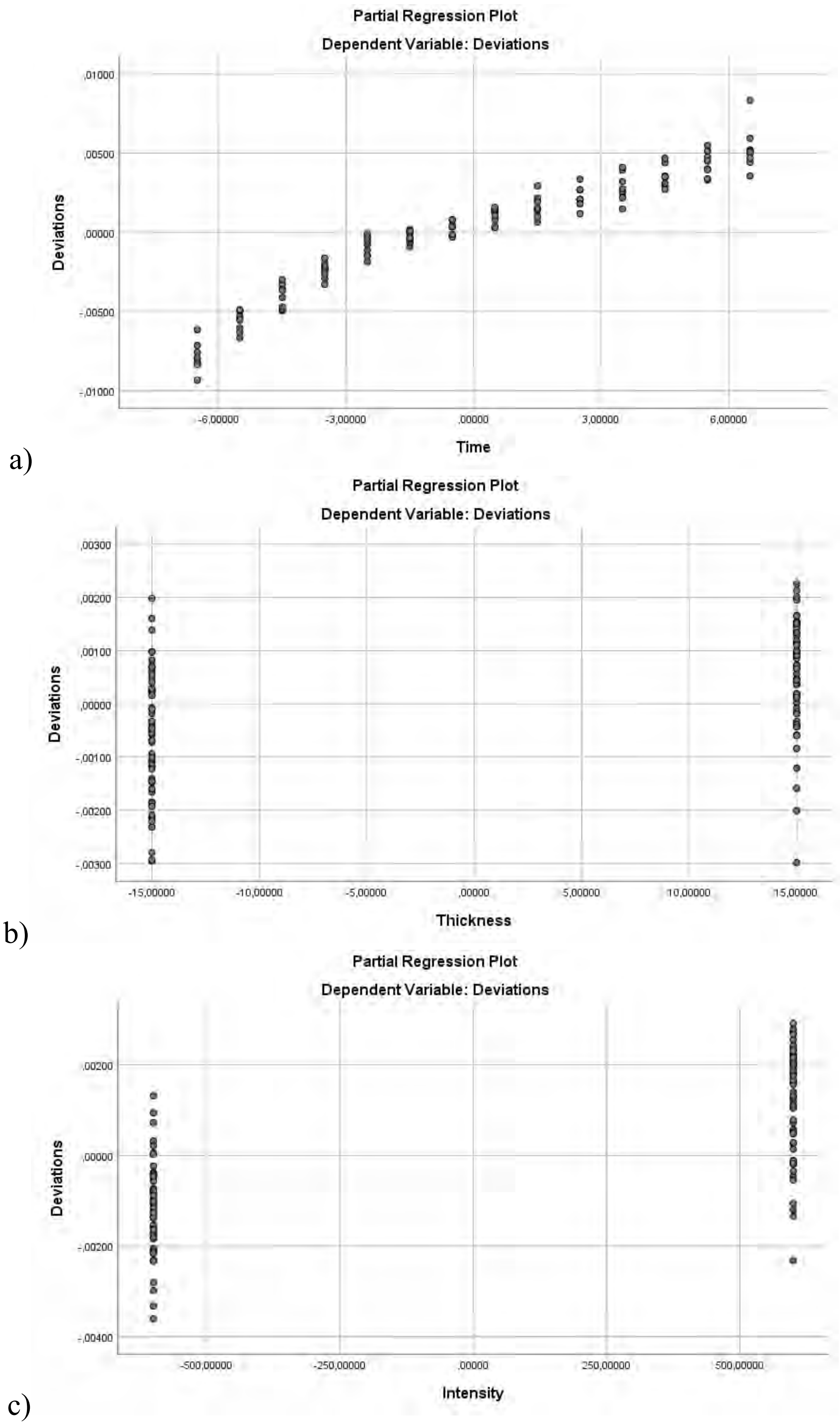

Fig. 16. Values of private regressions:
a – regression of deviations from the exposure time;
b – regression of deviations from the layer thickness;
c – regression of deviations from the exposure intensity

Building a model of multiple regression of the influence of exposure parameters on the geometric dimensions of a topology

We enter the data obtained into the IBM SPSS Statistics programme to conduct a basic linear regression analysis of the exposure parameters.

Using the "Summary for the model" calculations, we obtain the value of the coefficient of determination «*R*» – 0,962. This is an indicator of the correspondence between the values calculated by the model (linear regression) and the experimental results obtained, (fig. 17).

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,962[a]	,925	,922	,00111683	,925	441,002	3	108	,000

a. Predictors: (Constant), Intensity, Thickness, Time

b. Dependent Variable: Deviations

Fig. 17. Summary of models

For greater verification accuracy, we recalculate the result to the model with non-standardised predicted values and calculate the correlation of the parameters of deviation from the standardised values (calculated deviations), (fig. 18).

Correlations

		Deviations	Unstandardized Predicted Value
Deviations	Pearson Correlation	1	,962**
	Sig. (2-tailed)		,000
	N	112	112
Unstandardized Predicted Value	Pearson Correlation	,962**	1
	Sig. (2-tailed)	,000	
	N	112	112

**. Correlation is significant at the 0.01 level (2-tailed).

Fig. 18. Correlation of values

The value of «*R*» when re-calculated is 0,962, which proves that there is a correlation between the obtained and predicted values.

The coefficient of multiple determination «R^2» is 0,925. This means that the parameters included in the system have a 92,5% impact on the result. The adjusted «R^2» coefficient is 0,922 or 92,2%. The standard error of the estimate is 0,00111683.

Using the ANOVA table, we test the hypothesis that («R^2» = 0). Since the level of «Significance» is <0,05, the validity of the previous results is confirmed, (fig. 19).

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,002	3	,001	441,002	,000[b]
	Residual	,000	108	,000		
	Total	,002	111			

a. Dependent Variable: Deviations

b. Predictors: (Constant), Intensity, Thickness, Time

Fig. 19. Results of significance calculations

To determine the weight of each variable, we will use the "Beta coefficient", which shows how much the value of the parameter changes from an increase in one of the factors. To find the Beta coefficients, the calculation will be performed using standardised «Z-scores». This is necessary to make sure that the standardised values and non-standardised values coincide, (fig. 20).

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order	Correlations Partial	Correlations Part
1	(Constant)	7,533E-5	,001		,128	,898			
	Time	,001	,000	,904	34,178	,000	,904	,957	,904
	Thickness	3,575E-5	,000	,134	5,081	,000	,134	,439	,134
	Intensity	1,998E-6	,000	,300	11,359	,000	,300	,738	,300

a. Dependent Variable: Deviations

Fig. 20. Results of calculating the «Beta coefficients»

Based on the level of significance of the coefficients, it is possible to compare whether the «Beta coefficient» of a given factor is different from zero. In this case, all values of «Significance» are <0,05, which proves that all factors are included in the model correctly. The results of Pearson's correlations of factors on response (fig. 21).

The experiments show that when using the photopolymer 3D printing technology, it is possible to transfer the topology image to the PCB by combining the processes of applying the photoresist and simultaneously exposing the topology in one unit. During the experiments and the construction of a linear regression model, high-quality adhesion of the photopolymerised PCB to the surface of the workpiece was observed, as a result of which, during chemical etching, it was possible to avoid etching the ends of the tracks, in contrast to the results of using classical photoresist films, (fig 21).

Correlations

		Deviations	Time	Thickness	Intensity
Pearson Correlation	Deviations	1,000	,904	,134	,300
	Time	,904	1,000	,000	,000
	Thickness	,134	,000	1,000	,000
	Intensity	,300	,000	,000	1,000
Sig. (1-tailed)	Deviations	.	,000	,079	,001
	Time	,000	.	,500	,500
	Thickness	,079	,500	.	,500
	Intensity	,001	,500	,500	.
N	Deviations	112	112	112	112
	Time	112	112	112	112
	Thickness	112	112	112	112
	Intensity	112	112	112	112

Fig. 21. Results of Pearson correlation calculations

Based on the obtained values of the «Beta-coefficients», the following conclusions can be drawn:

– an increase by one unit of time results in an increase in the value of dimensional deviation by 0,904;

– an increase of one unit of radiation intensity leads to an increase in the value of dimensional deviation by 0,3;

– an increase of 30 units of thickness leads to an increase in the value of dimensional deviation by 0,134;

This proves that time is the most important factor in 3D exposure. The regression equation looks like this:

$$Y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 = 0,002 + 0,904 x_1 + 0,134 x_2 + 0,3 x_3,$$

where Y is the factor of deviation of the geometric dimensions of the PCB topology; b_0, b_1, b_2, b_3 are the coefficients of linear regression of the influence of parameters on the factor; x_1, x_2, x_3 are the parameters of influence on the factor.

Conclusions

The paper presents practical results related to the creation of printed circuit board topology using photopolymer exposure of the conductor structure. A general procedure for converting a 2D PCB topology into a 3D format for photopolymer printing is proposed. The parameters that can affect the deviation of the geometric dimensions of the topology in this production are considered. The obtained efficient values of 112 samples were verified. The optimal exposure values with the minimum values of topology deviation are revealed. A model of multiple regression of the influence of exposure parameters on the deviation of geometric dimensions of the topology was built.

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