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RESEARCH OF ELECTRIC PULSE TREATMENT OF RHOZOMES OF MANY FLYING WEEDS BY FACTORIAL EXPERIMENT METHOD

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Abstract
The article presents the results of studies on the study of the electrical resistance of the degree of damage Rd.d (an assessment indicator of the condition of living tissues) that occurs when one of the following factors changes: U - discharge voltage; kV; τti - processing time, s; I - discharge current, A; F - shape and size of rhizomes; h - interelectrode space (the distance between the positive and negative electrodes where the plant tissue of the humai is located); C is the capacity of the storage capacitor, F; P - chemical and biological components in the electric pulse treatment of weeds.
The research examined the data U, I, τti and Rd.d, which contain variable values and have the most significant indicators. Histograms were constructed to visualize the distribution of each variable and a regression model line was constructed covering all combinations of variables U, I and τti to the third degree, which allows one to assess their influence on the dependent variable Rd.d.

Keywords: electric current, high voltage, pulse discharges, electrical resistance of the degree of damage, interelectrode space, storage capacitor capacity, weeds, rhizomes of many summer weeds.

Introduction

In laboratory conditions, there are certain difficulties in determining the influencing factors on the degree of damage to gum grass and pigweed and reed when the values of U, τ and I are fixed. For this reason, in this work there was a need to conduct additional experimental studies using the factorial experiment method [1, 2, 3, 4].
The optimization parameter is the electrical resistance of the degree of damage Rd.d. In this case, we proceeded from a priori information and the results of previous studies. To obtain a mathematical model of the process of electric pulse treatment of rhizomes of perennial weeds gumaya, it is necessary to establish factors taking into account the requirements for them [1, 2, 3].
During electric pulse treatment of plant tissue of weed rhizomes, various factors of electrical energy of a thermal, electromagnetic, electropulse, electro-hydraulic nature influence Rd.d. which arise when one of the following factors changes: U - discharge voltage; kV; τti - processing time, s; I - discharge current, A; F - shape and size of rhizomes; h - interelectrode space (the distance between the positive and negative electrodes where the plant tissue of gumaya rhizomes is located); C is the capacity of the storage capacitor, F; P - chemical and biological composition [3, 4, 5, 6,].

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2. Experiment and methods for solving them

This study examines a data set containing the variables U, I, τi and $R_{d.d}$ (Table 1). The purpose of the study is to determine the relationship between these variables using quadratic regression.

We analyze data that has a possible impact on damage to plant tissue and the electrical resistance of the degree of damage. The data set consists of four variables: U, I, τ_{ti} and $R_{d.d}$ since they are the most significant.

For each of them, a preliminary analysis was carried out to understand their distribution and relationships.

1. Descriptive Statistics: This involves calculating the mean, median, standard deviation, minimum and maximum values for each variable. These metrics help you understand overall trends and data dispersion.

2. Distribution analysis: assessing the shape of the distribution of each variable, for example using histograms. This helps determine whether a variable follows a normal distribution or has distortions such as skewness. In our case, histograms were constructed to visualize the distribution of each variable (Fig. 1). Histograms help you understand the shape of a distribution and identify possible asymmetries or anomalies.

Table 1. Initial data influencing factors on the electrical resistance of the degree of damage ($R_{d.d}$)

№	*U* (kV)	*I* (A)	τi (s)	$R_{d.d}$ (Om•mm^2)
1	9	0,015	0,4	1,5
2	9	0,001	0,4	2,06
3	5	0,015	0,4	1,94
4	5	0,001	0,4	1,86
5	9	0,008	0,6	1,63
6	9	0,008	0,2	2,02
7	5	0,008	0,6	1,81
8	5	0,008	0,2	1,77
9	7	0,015	0,6	1,03
10	7	0,015	0,2	1,6
11	7	0,001	0,6	1,34
12	7	0,001	0,2	1,54
13	7	0,015	0,4	1,06
14	7	0,008	0,4	1,02
15	7	0,008	0,6	1,05

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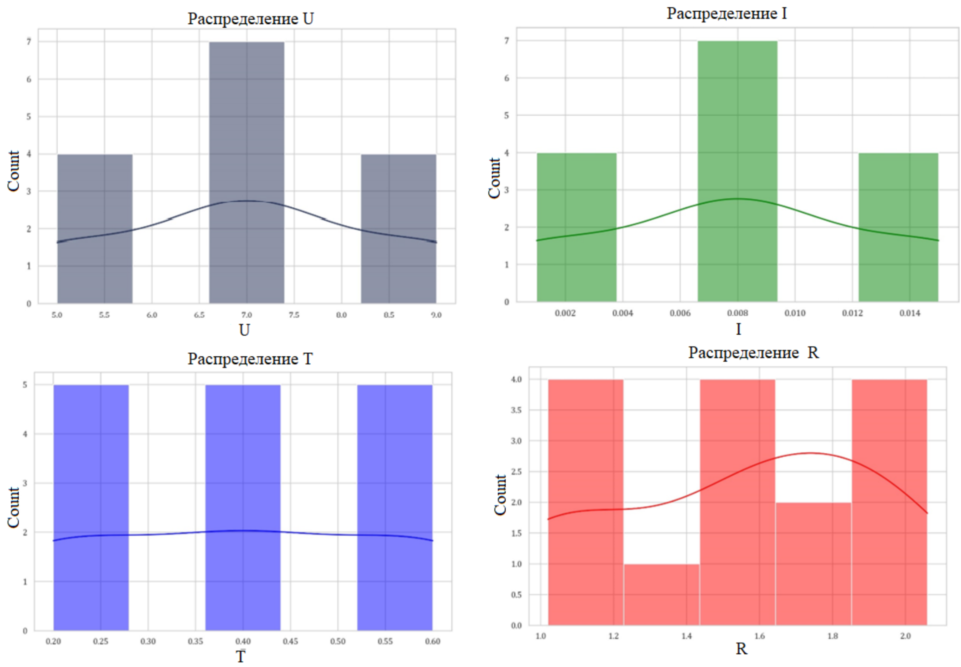

Figure 1. Histograms to visualize the distribution of each variable.

3. Correlation analysis: The study of correlation relationships between variables. This can be done using a correlation matrix or scatterplots. Correlation analysis helps identify possible linear relationships between variables.

4. Check for outliers: Outliers can distort the analysis results, so it is important to identify them. This can be done using visual analysis, such as using a boxplot, or using statistical methods. Using boxplots (Figure 2), a visual assessment of the presence of outliers for each variable was carried out. These charts help you identify values that are very different from the rest of the data.

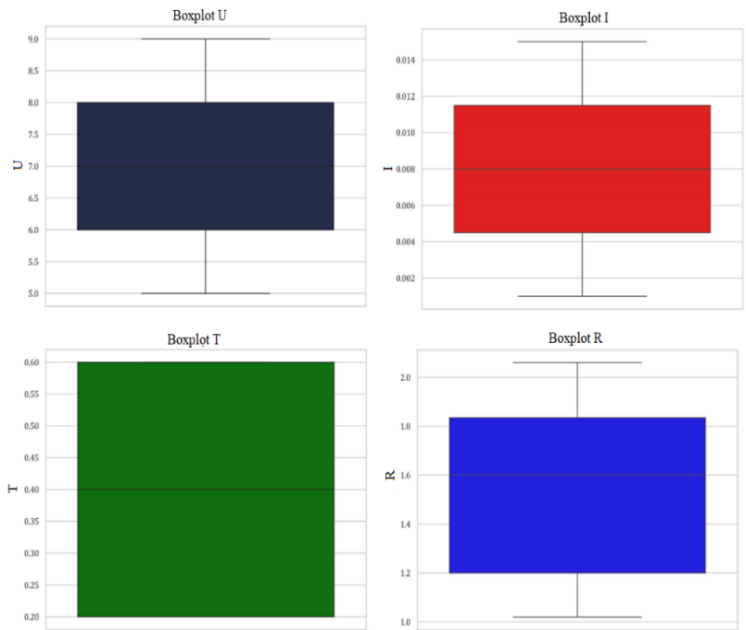

Figure 2. Box plot

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3. Results and discussions

Taking into account the above, a regression model of the process and the degree of damage to plant tissues was built, consisting of the following sequence [3, 4, 7].

1. Model selection: to analyze the relationship between the variables U, I, τi and $R_{d.d}$, a quadratic regression model was selected. It is due to the fact that quadratic regression allows taking into account not only linear, but also more complex nonlinear dependencies between variables [3].

2. Transformation of Variables: Before building the model, it was necessary to transform the original data. To do this, the variables U, I and τi were transformed into polynomial features up to the third degree (quadratic terms), which made it possible to include linear, quadratic and quadratic interactions between these variables in the model.

3. Model building: Using the transformed data, a linear regression model was built. The model includes all combinations of variables U, I and τi up to the third degree, which made it possible to assess their influence on the dependent variable $R_{d.d}$.

4. Assessing the significance of the coefficients: after building the model, the regression coefficients were estimated. This involved analyzing the significance of each coefficient to determine which ones had a significant effect on the dependent variable. Coefficients with low significance (close to zero) were excluded from the model for simplicity.

5. Interpretation of the Results: Based on the obtained coefficients, the final model was formed. This model allows us to evaluate how changing the values of the variables U, I and τi affects the value of $R_{d.d}$, taking into account the complex interactions between these variables.

The quadratic regression model was quite complex due to the large number of terms included, but it provides greater insight into the relationships between variables than a simple linear model.

Evaluation of the model for suitability for the process of electrical processing of plant organisms. Evaluating a regression model is a key step in determining how well the model fits the data and can be used to make predictions. Therefore, various methods and criteria are used, consisting of the following sequences [3, 4, 7]:

1. Mean Square Error (MSE): MSE is the average of the squared errors between the actual and predicted values. A lower MSE value indicates a better fit of the model to the data. Formula for MSE [3]:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left|y-\hat{y}\right|, \tag{1}$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, n is the number of observations.

2. Coefficient of Determination (R^2): R^2 measures how much of the variance in the dependent variable is explained by the independent variables in the model. An R^2 value close to *1* indicates a high degree of model fit. Formula for R^2 [3]:

$$R^2 = 1 - \frac{1}{n}\cdot\frac{\sum_{i=1}^{n}\left|y_i-\hat{y}_i\right|}{\sum_{i=1}^{n}\left|y_i-\bar{y}_i\right|}, \tag{2}$$

where $\bar{y}$ is the average value of y.

3. Residual Analysis: Residual analysis (the difference between actual and predicted values) helps determine how well the model performs for different observations. An ideal model should have residuals randomly distributed around zero [3].

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4. Check for overfitting: It is important to ensure that the model is not overfitting on the original data. Overfitting means that the model is overfitted to the original data set and may not perform well on new data. To check for overfitting, you can use cross-validation methods [4].
5. Significance Analysis of Coefficients: Testing the statistical significance of a model's coefficients, usually using a t-test, helps determine which variables are truly important to the model [3].
In our case, the model was estimated using MSE and R^2, and a model simplification procedure was carried out by eliminating insignificant coefficients. The obtained MSE and R^2 values indicated the high accuracy and adequacy of the model [3].
The model was evaluated using mean square error (MSE) and coefficient of determination (R^2). The obtained values of MSE = 0.022 and R^2 = 0.944 indicate the high accuracy of the model. This means that about 94.4% of the variation in the dependent variable $R_{d.d}$ is explained by the variation in the independent variables U, I and τ_{ti} in the model (Table 2, Fig. 3).

Fisher test (F-statistic and Prob (F-statistic):
- F-statistic: 9.426
- P-value for F-statistic: 0.012

Analysis of variance:
- Regression Sum of Squares (SSR): 1.834
- Sum of Squared Errors (SSE): 0.108
- Mean square error (MSE): 0.022
- Mean Square Regression (MSR): 0.204

As a result of simplifying the model, the following final formula was obtained:

$$R_{d.d.} = 0{,}808 - 2{,}130 \cdot U + 17{,}474 \cdot I - 1{,}290 \cdot \tau_{ti} - 0{,}166 \cdot U^2 - 11{,}429 \cdot U \cdot I -$$
$$- 0{,}269 \cdot U \cdot \tau_{ti} + 4744{,}898 \cdot I^2 - 66{,}071 \cdot I \cdot \tau_{ti} + 3.950 \cdot \tau_{ti}^{\ 2}$$

This formula reflects the relationship between the variables U, I, τ_{ti} and $R_{d.d}$ within the data set under study (Table 3).

Table 2. Model coefficients, standard errors of coefficients, τ-statistics and P-values for each coefficient:

Coefficient	Model Coefficients	Standard Errors	τ_u - Statistics	P-Values
Intercept (a0)	8.808	-	-	-
a1	0.000	0.787	0.000	1.000
a2	-2.130	0.179	-11.902	0.000074
a3	17.474	29.529	0.592	0.579745
a4	-1.290	1.370	-0.942	0.389657
a5	0.166	0.012	13.517	0.000040
a6	4744.898	1000.231	4.744	0.005133
a7	3.950	1.397	2.827	0.036787
a8	-11.429	3.032	-3.770	0.013029
a9	-0.269	0.106	-2.533	0.052358
a10	-66.071	30.318	-2.179	0.081186

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Note. This table provides a complete picture of the model parameters and their statistical significance.

The graph shows a comparison of the measured values of $R_{d.d.meas}$ (along the abscissa) and the predicted values of $R_{d.d.calc}$. (along the ordinate) using a linear regression model. The trend line shows the relationship between measured and predicted values (Figure 3).

The information in the upper left corner provides details of the statistical analysis:

• Trend line equation: $y = a + bx$ where a (intercept) is close to zero (-0.00296) and *b* (slope) is close to 1 (1.00191), indicating that the predicted values are very close to the measured values.

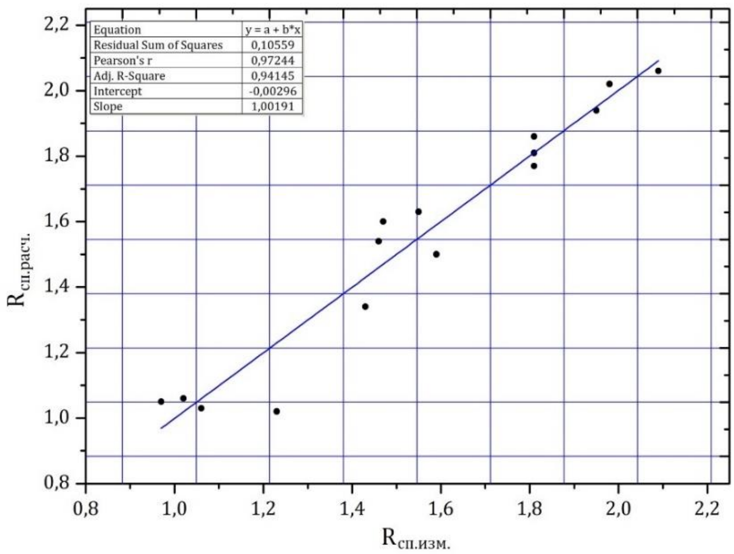
• Sum of squared residuals: 0.10559, which represents the overall error of the model.

• Pearson correlation coefficient: 0.97244, shows a strong linear correlation between measured and predicted values.

• Adjusted coefficient of determination (Adj. R-Square): 0.94145, confirms that the model explains most of the variation in measured values.

Table 3. Model results for determining $R_{d.d.}$

№	*U*, kV	*I*, A	τ_u, c	$R_{d.d.meas}$	$R_{d.d.calc.}$
1	9	0.015	0,4	1,50	1,59
2	9	0.001	0,4	2,06	2,09
3	5	0.015	0,4	1,94	1,95
4	5	0.001	0,4	1,86	1,81
5	9	0.008	0,6	1,63	1,55
6	9	0.008	0,2	2,02	1,98
7	5	0.008	0,6	1,81	1,81
8	5	0.008	0,2	1,77	1,81
9	7	0.015	0,6	1,03	1,06
10	7	0.015	0,2	1,60	1,47
11	7	0.001	0,6	1,34	1,43
12	7	0.001	0,2	1,54	1,46
13	7	0.008	0,6	1,06	1,02
14	7	0.008	0,2	1,02	1,23
15	7	0.008	0,4	1,05	0,97



Rice. 3. Comparison graph of measured values $R_{d.d.meas.}$ to the calculated $R_{d.d.calc.}$

The black dots in the graph represent individual observations. The proximity of points to the trend line indicates a good fit between the model and the data.

CONCLUSIONS

1. Analysis of the graph makes it possible to compare the measured values of resistance to the degree of damage $R_{d.d.meas}$ with the predicted values $R_{d.d.calculated}$ resistance to the degree of damage to plant tissues, which shows the correctness of the selected processing parameters, as evidenced by the trend line of the relationship between the measured and predicted values.
2. Trendline equation: y=a+bx, where a (intercept) is close to zero (-0.00296) and b (slope) is close to 1 (1.00191), indicating that the predicted values are very close to the measured ones .
3. Sum of squared residuals: 0.10559, which represents the overall error of the model which does not exceed acceptable values.
4. Pearson correlation coefficient: 0.97244, shows a strong linear correlation between measured and predicted values.
5. Adjusted coefficient of determination (Adj. R-Square): 0.94145, confirms that the model explains most of the variation in the measured values.

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