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ARTIFICIAL AND COMPUTATIONAL INTELLIGENCE

Improvement of unmanned aerial vehicles model under surge of lightning electromagnetic pulse developed using artificial intelligence based on laboratory measurements in reference to classical regression methods

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Abstract. Unmanned aerial vehicles (drones) are increasingly used in a growing number of applications, both civil and military. Their design is based on low weight, making the presence of shielding a difficult decision between safety and weight. Currently, there are no mathematical models to determine the safety of drones operating near a storm front. Lightning causes an electromagnetic wave of an impulse nature, which may pose a real threat to electronic systems. This work attempts to develop a mathematical model for simulating drone safety in terms of electromagnetic pulses using artificial intelligence-based tools. Actual measurement results collected from four drones were used as training data. They were tested in laboratory conditions using specialized measuring equipment used to test avionics in accordance with international standards such as DO-160. A repeatable surge pulse generator and a data acquisition system allowed us to collect information on how overvoltages propagate inside the drone systems. Systems that directly influence its operation were selected for this purpose, such as the power supply system, engine controllers, GPS, camera and data bus lines. Other works show that most overvoltages are induced in motor coils and antennas. On this basis, a number of formulas and equations were developed to describe the most important elements of the drone, without which its correct operation would not be possible. The results of the analyses and the mathematical model of the drone based on the examined cases are presented in this work as a complement to real experiments.

Keywords: machine learning; lightning discharges; mathematical model; transmittance of drone circuits.

1. INTRODUCTION

Unmanned aerial vehicles (UAVs) find many applications, especially in areas where they can support people in their work [1,2]. These are precise measurement and diagnostic tools that are used in many industries [3]. They also have a number of military applications, especially visible recently during numerous military operations in Europe. It is impossible to list all the possibilities and applications because the number of solutions is growing very quickly [4, 5]. However, you should consider the safety of such facilities. Among many threats, such as strong wind, rain, or birds, there is electromagnetic interference from many sources. In addition to intentionally disrupting the operation of such machines, the greatest threat is the electromagnetic pulse (EMP) generated by lightning [6]. Regardless of whether it is a ground discharge or cloud-to-cloud discharge (regardless of the polarization of this discharge), an electromagnetic impulse is generated from the lightning discharge as a result of a current flow (higher than hundreds of kA) in the lightning channel [7, 8]. Lightning electromagnetic pulse (LEMP) affects all electrical and electronic systems, causing overvoltages to occur in them that can damage these circuits [9, 10]. Therefore, it is very important to use appropriate shields in facilities exposed to lightning strikes in close proximity.

One way to determine the effects of lightning on unmanned aerial vehicles is to conduct experimental research. This is the most effective and reliable method to test a finished drone to determine its resistance. However, it is expensive, and a negative result may require the design of the structure from scratch or the introduction of significant modifications, in particular in terms of electromagnetic protection. The second solution is to perform simulations on drone models. The problem may be the correct mathematical description of the device. Each UAV has a slightly different structure, especially in terms of the electronics used [1, 5]. This means that each case must be developed independently. Developing the right model may not be easy, but this article proposes one possible solution that allows us to collect data to build the model without damaging the physical prototype. This made it possible to use tools based on artificial intelligence to develop an appropriate mathematical model of

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the tested drone. The general idea was to determine the transmittance of many different drone circuits, especially those that can transfer interference from less to more sensitive points. Determining the transmittance of related circuits facilitates analyzing the signal flow in the developed fragments divided into blocks. The model developed in this way can be used for further analysis and simulations to determine the distance from a lightning discharge at which its damage may occur. Additionally, it is possible to determine which of the components poses the greatest threat to its proper operation. By overlaying this model with data related to shielding such structures, it would be possible to determine which fragments should be particularly protected and how. The use of such models can help in the subsequent design and improvement of the structure, especially when developing a given model for other applications. The biggest novelty in the proposed method is the use of neural networks to develop the UAV model, which is to ensure a higher coefficient of determination compared to classical methods such as linear or polynomial regression.

This article proposes a noninvasive measurement method related to collecting data on the electrical parameters of individual drone circuits. In typical lightning resistance tests the drone is placed inside a homogeneous field or near a conductor that serves as an antenna [11]. In such studies, overvoltages are generated in all circuits at the same time and it is not possible to develop a transmission model of individual blocks. Direct testing of such a device is also possible, but it is usually destructive. In the proposed solution, it was decided to use low voltage to avoid damage to the electronics, which ensured the repeatability of the recorded results. This data was then used to create a model using artificial intelligence tools. The data was compared with well-known prediction methods such as linear, nonlinear, or polynomial regression. The conclusions were then collected, and the proposed issue was summarized.

2. ARTIFICAL INTELIGENCE METHODS AND TOOLS

Artificial intelligence (AI) tools are currently among the fastest growing in the world [12–14]. This work focuses on one narrow aspect of this tool, namely data prediction. Among many publications, we can find those devoted to predictions related to medicine [15–17], predicting natural disasters [18], determining flood risk [19], water processing [20], image processing [21] or industry [22]. However, no publications related to the prediction of overvoltages induced in drone circuits due to the impact of LEMP were found. Most often, artificial intelligence is used to predict flight or determine routes for swarms of many drones [23, 24]. We can also find information about general development trends [25]. However, no one has attempted to develop a mathematical model of the drone using artificial intelligence tools, so it was decided to propose an innovative solution as an introduction to further development of the work.

There are many different tools for predicting results based on data samples, including:

- Support vector machines (SVM) [26];
- Decision trees and random forests [27];
- Gradient boosting [28];
- Recurrent neural networks (RNN) [28];
- Convolutional neural networks (CNN) [29];
- Autoencoders and generative networks (GANs) [30];
- Reinforcement learning (RL) [31].

Equation (1) represents the output of a single neuron in a neural network (NN) defined by [32]:

$$y = f\left(\sum_i w_i x_i + b\right), \tag{1}$$

where y is the output of the neuron, f is the activation function, w_i are the weights of the inputs, x_i are the input values, b is the bias term.

For NN with "l" ($2 \le l$) hidden layers, the equations are very similar, but are repeated for each layer [32–34]. Input layer to first hidden layer (equation (2)):

$$Y^{(1)} = f(W^{(1)}X + B^{(1)}). \tag{2}$$

Between layers (equation 3):

$$Y^{(l)} = f(W^{(l)}Y^{(l-1)} + B^{(l)}). \tag{3}$$

Last hidden layer to output layer (equation (4)):

$$Y^{(N+1)} = f(W^{(N+1)}Y^{(N)} + B^{(N+1)}), \tag{4}$$

where $Y^{(l)}$ is the output vector for layer l, f is the activation function, $W^{(l)}$ is the weight matrix for layer l, X is the input vector, $B^{(l)}$ is the bias vector for layer l.

Many of the above methods can be found in ready-to-use tools or libraries. Implementation can be done in Python (as a multilayer perceptron neural network) or MATLAB (Deep Learning Toolbox). The use of a programming environment allows for the precise development of a computational model, determining the scope of training and test data, thresholds determining the end of iteration processes, data validation, and many specific parameters, such as the number of neurons in the network being created. For quick calculations that do not require specific programming knowledge, you can use sample tools available online, e.g., Smodin Omni [35], Photomath [35], or Math AI [36].

However, they do not provide full possibilities, which is why the MATLAB environment and libraries related to neural networks were used in this work. The program allows you to use built-in functions and efficiently build appropriate models based on a user-defined number of neurons and training data. However, in order to develop a model, data had to be collected from a real device. The data was then fed into a MATLAB neural network model to develop the results. The simulations were conducted in the Matlab environment, version R2023b, on a computer with an Intel Core i5 1035G1 processor using 8GB RAM. Neural networks are a key element of artificial intelligence. They are inspired by the structure and functioning of the human brain and are used to model complex patterns and decision-making processes [12]. Neural networks are the basis of many advanced AI technologies, such as deep learning, so this is a decision to use them for this issue. The MATLAB library for neural networks is the Deep Learning Toolbox [37]. This library provides Simulink functions, applications, and blocks for the design, implementation, and simulation of deep neural networks. It allows you to create and use many types of networks, such as convolutional neural networks (CNN) and transformers [37].

3. MEASUREMENT EQUIPMENT SETUP

Each of the important elements of the drone was examined using a shock pulse as an input (input signal), and the signal at the output of this circuit was measured. Thanks to this, it was possible to determine the transmittance of each circuit, i.e., the ratio of the Laplace transform of the output signal to the Laplace transform of the input signal of the system under zero initial conditions (equation (5)) [38]. Transmittance is the frequency model of the system (in its basic form defined in the s domain). It determines the general properties of a stationary linear system with one input and one output, independent of the type of excitation [38, 39].

$$T(s) = \frac{Y(s)}{X(s)}, \tag{5}$$

where $T(s)$ is the transfer function, $Y(s)$ is the Laplace transform of the output signal, $X(s)$ is the Laplace transform of the input signal.

In order to be able to calculate the transmittance of individual parts of the drone, the most sensitive parts of the drone electronics must be selected, through which the overvoltage will propagate to other systems. The elements most susceptible to LEMP induction are motors, antennas, and power supplies [11, 40]. From there, the overvoltages can be transmitted to all critical components such as the GPS, RF transmitter, gyroscope, or main CPU. Therefore, it was decided to analyze the propagation of signals from common lines that allow for the propagation of overvoltages to those that are more sensitive but less susceptible to inducing interference (due to their small size and short paths). Figure 1 shows a block diagram containing the most important electronic systems of the drone. The measurements were made by injecting a surge pulse into a given measurement point (marked with a number in Fig. 1), and then the output voltage was measured at another point. Thanks to this, it was possible to measure the physical parameters of a given set of electronic components that constitute the propagation path of the overvoltage to the selected system (e.g., GPS module) [41, 42]. The components used to collect the data (this number of points will be used throughout the paper):

- Point 1 – battery power supply (7.4 V);
- Point 2 – integrated circuits power supply (3.3 V);
- Point 3 – data bus to GPS module (USART);
- Point 4 – data bus to camera (I^2C);
- Point 5 – data bus to gyro (inside EMC cover);
- Point 6 – radio frequency antenna;
- Point 7 – modulation signal line to electronic speed controller (ESC);
- Point 8 – motor coil (connection between brushless motor and ESC);
- Point 9–12 – four point in elctronic devices under EMC cover.

Using the transmittance formula (5), we obtain a mathematical description. If we divide the numerical values of the output voltages by the input voltages at given moments of time (as single samples), we will only obtain a numerical relationship between them. However, the value of transmittance in the Laplace domain, that is, related to the frequency of the pulse tested, is important [38, 43]. Therefore, the measured pulse data was used for analysis using neural networks. The aim was to determine the exact parameters of the tested object, which in the future could help to create a comprehensive base model developed on the basis of other models of such devices.

The measurement scheme is presented in Fig. 2. The excitation was a shock pulse from the MIG0618SS generator (single-

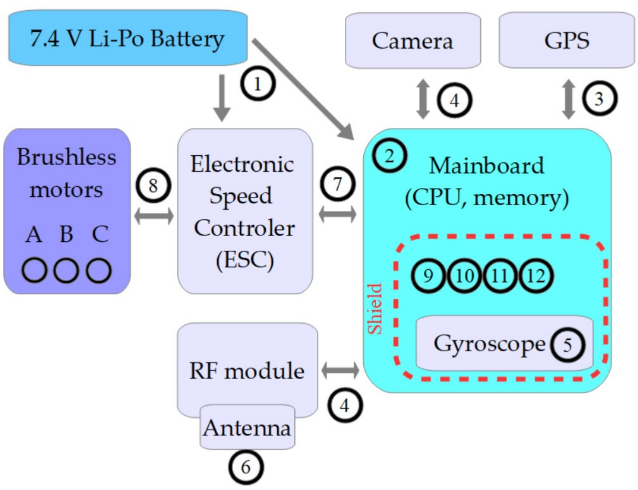

Fig. 1. Main parts of the UAV with measuring points

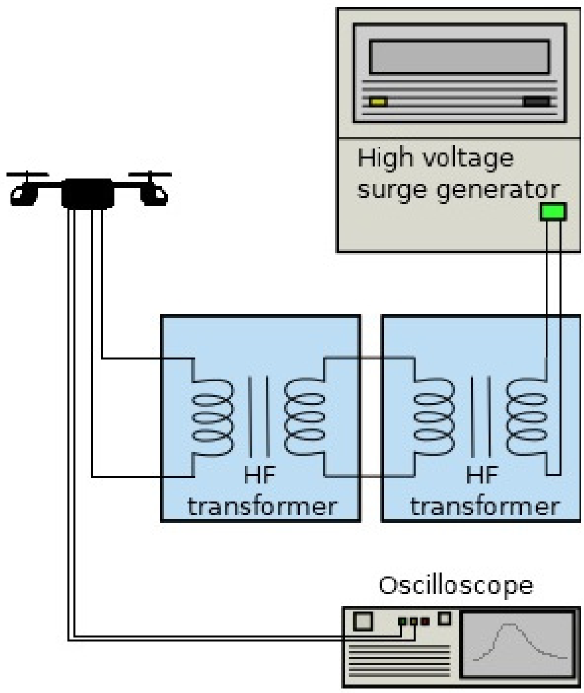

Fig. 2. Measurement setup for collecting the data for AI analysis

stroke voltage impulse). It is a pulse standardized according to the international standard RTCA-DO-160 and others [44–46] related to the testing of electronic devices for lightning in aviation. The pulse has an equal 6.4 µs rise time and an equal 69 µs fall time. This generator ensures full repeatability of the generated waveform, which ensures precision of measurements. The surge pulse generator was connected via dedicated transformers (see Fig. 2) that reduced the voltage five times. The lowest possible voltage that can be set in the generator is equal to 125 V. The use of voltage reduction stage allowed to obtain an impulse with a peak voltage of 25 V. Such a low voltage allowed us to conduct tests using the "pin injection" method, i.e., direct injection of a surge pulse into the tested system. Reducing the maximum voltage to 25 V allowed us to measure the impulse response of many circuits and to conduct several repetitions while limiting the risk of damaging the UAV electronics. Using a higher surge voltage would result in damaging the semiconductors during the first test and changing the tested object, making it impossible to conduct further tests. The recording device was a RIGOL 1154Z oscilloscope with a bandwidth of 100 MHz and sampling 1Gs. The basic frequency due to the edge rising time is approximately 150 kHz. A measurement window of 60 µs was recorded, which provided information about the most important part of the stroke and the impulse response of the tested electronic systems while ensuring high measurement resolution. Figure 3 shows an example of the time course of a surge impulse measured at the input terminals of the UAV power supply and at the IC supply as the system impulse response. The lower value of the peak voltage results from the connected load in the form of drone electronics. The shape of the waveform can be observed consistent with the previous description.

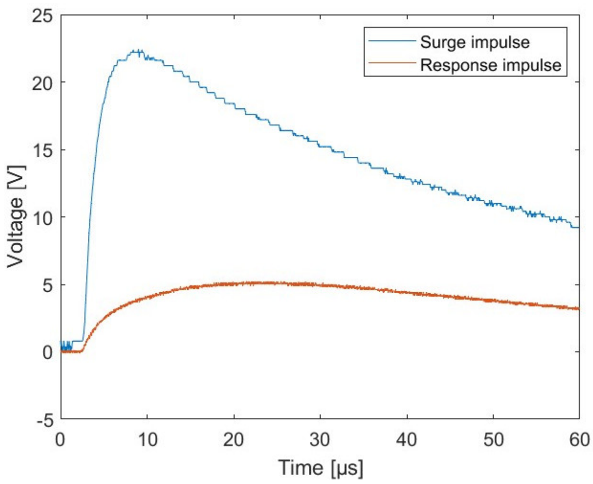

Fig. 3. Surge pulse measured in input (UAV power supply) and output (IC supply) as response

The repeatability of the measurement results was possible thanks to the use of the MIG0618SS generator, which allowed for generating the same pulse shape during each measurement. In addition, reducing the surge voltage allowed the drone to remain operational after the tests were completed. Thanks to this, the entire test process was carried out under repeatable and identical conditions, guaranteeing the correct measurement results. Based on previous studies of many other UAVs, the analyzed results are similar due to the similar construction of these devices [11]. However, there are exceptions for other components or specific solutions. As in every case, the proposed solution is not a completely universal solution because this was not the aim of the investigation. This article focuses on the possibility of using artificial intelligence tools to help develop a more accurate model than previously used techniques, such as linear or polynomial regression.

4. NEURAL NETWORK SIMULATIONS RESULTS

Deep Learning Toolbox in MATLAB was used to analyze the data. Thanks to the possibility of adjusting many parameters, such as: network architecture, network size, data scope, division into training, verification and test data, or verification of network results, it is possible to optimize the entire process in terms of the characteristics of the tested impulses. For the entire data analysis process using AI, a total of 45 600 samples were collected, divided according to the place of excitation and the parts of the drone electronics tested. This number represents all pairs of input voltage and corresponding output voltage values versus time for 38 test runs. Each run consists of 1200 samples, with each measured value every 50 ns. The detailed division is included in Table 1. The number of inputs and outputs refers to the number of elements included in the drone construction diagram (Fig. 1). Measuring point number 2 is the electronics supply voltage (3.3 V) and is separated from the supply voltage by a voltage stabilizer system. Points 9–12 (referred to as "hidden") are randomly selected points under the electromagnetic shield used by the manufacturer. The aim of this study was to determine the magnitude of overvoltages occurring in areas of electronics that are under special protection (EMC shield). Measurement point No. 5 (communication line to the gyroscope) was also undercover (independent of the one described earlier).

Table 1
Input and output points for collecting the data (see Fig. 1)

No	Input point	Output points	Number of samples
1	1	2, 3, 4, 5, 6, 7	14400
2	6	1, 2, 3, 4, 5	12000
3	8	1, 7	4800
4	7	2	2400
5	2	1, 9, 10, 11, 12	12000

All data was collected for positive and negative polarization of the shock pulse for each of the measurement pairs (input-output). This corresponds to real lightning conditions, in which most (90%) are negatively polarized [47]. However, a positive discharge cannot be ruled out, and polarization has a decisive impact on the propagation of overvoltages through semiconductor elements.

Data analysis parameters:
- Lavenberg-Marquardt training method;
- Mean squared error (MSE) performance;
- 50% of data – training samples;
- 25% of data – testing samples;
- 25% of data – validation samples;
- 10 neurons in hidden layer;
- Maximum 100 epochs.

The input data was sets of measurement points as a function of time (pairs of input and output voltages of the system under test, as indicated earlier) for many repetitions of the surge pulses (the list of input and output points and the number of samples is summarized in Table 1). The neural network built within the Deep Learning Toolbox library requires an equal amount of input data and corresponding output data to process the results.

For the first item in Table 1, the results of the calculations using the neural networks tool in the MATLAB environment are presented. This is the most important path for propagating overvoltages because the power line affects most components. Results were shown in Figs. 4–6.

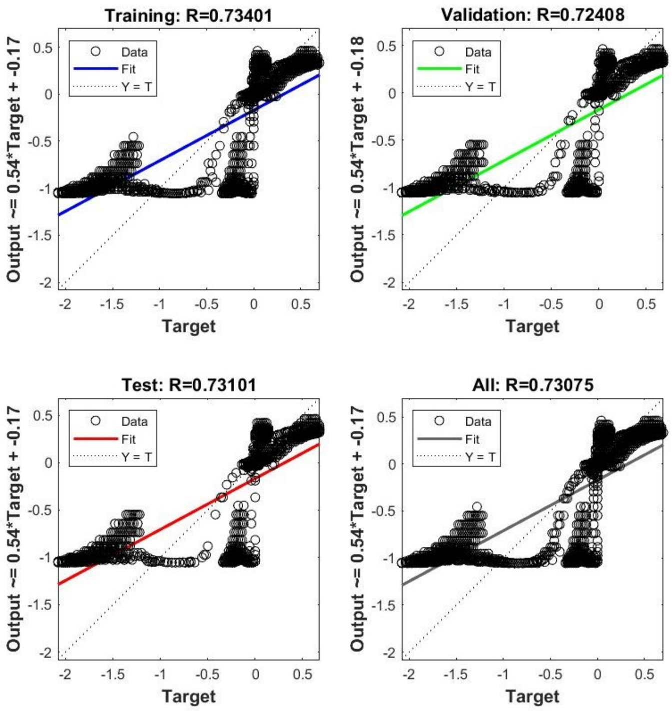

Fig. 4. Neural network regression

The second most important aspect was then examined, the propagation of overvoltages in integrated circuits and data buses (3.3 V). In this way, overvoltages can propagate to the most sensitive electronic systems powered by the lowest voltage level. The results were shown in Figs. 7–9.

The results for the remaining paths (including the previous ones) are summarized in Table 2. Table 2 also compares the results with:

- Linear regression;
- 4th order polynomial equation;

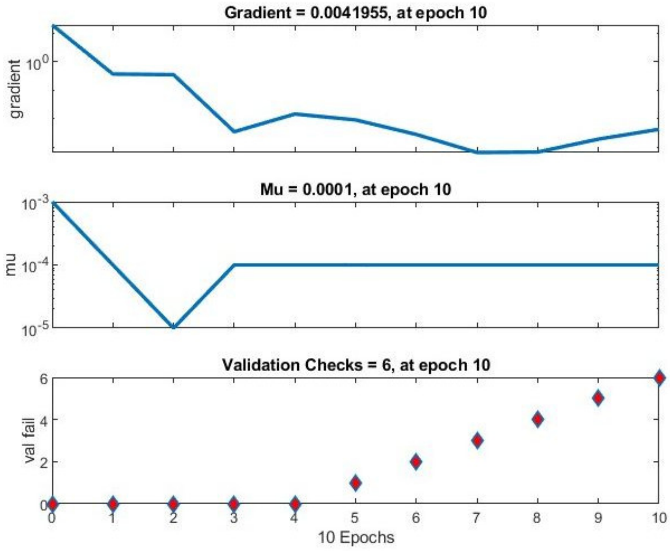

Fig. 5. Neural network training state

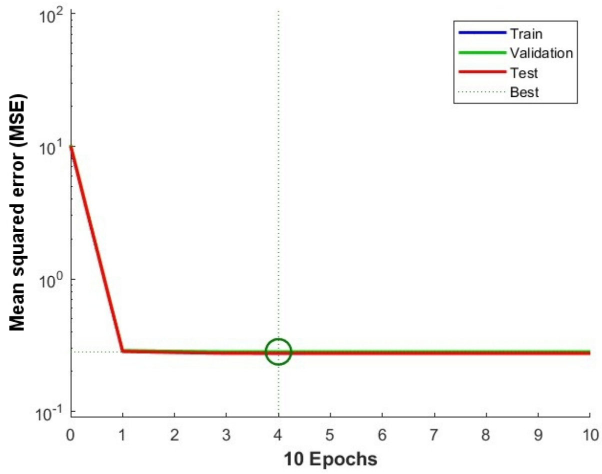

Fig. 6. Neural network training performance

- Nonlinear regression method using equation (6):

$$y = a \cdot e^{b \cdot x} + c. \tag{6}$$

The coefficient of determination converted into percentages was used to compare the results obtained by training the neural network with other methods. It determines the accuracy of mapping the developed model (or formula in the case of linear or polynomial regression) to raw data.

An example of an approximation using a linear and polynomial function using libraries and functions available in the MATLAB environment is presented in Fig. 10.

However, the complexity of the model is not a problem because the created neural network structure can be used to further develop simulation tools. A purely mathematical description is therefore not necessary because, on the basis of the calculations, a specific neural network was obtained to calculate the given problem.

Table 2
Compare results of neural network and other methods (see Fig. 1)

			Coefficient of determination calculated in percent value (%)			
No	Input point	Output points	Neural network	Linear regression	Polynomial regression	Nonlinear regression
1	1	2, 3, 4, 5, 6, 7	73%	49%	52%	49%
2	6	1, 2, 3, 4, 5	56%	29%	31%	31%
3	8	1, 7	96%	31%	52%	31%
4	7	2	61%	3%	29%	8%
5	2	1, 9, 10, 11, 12	86%	72%	73%	73%

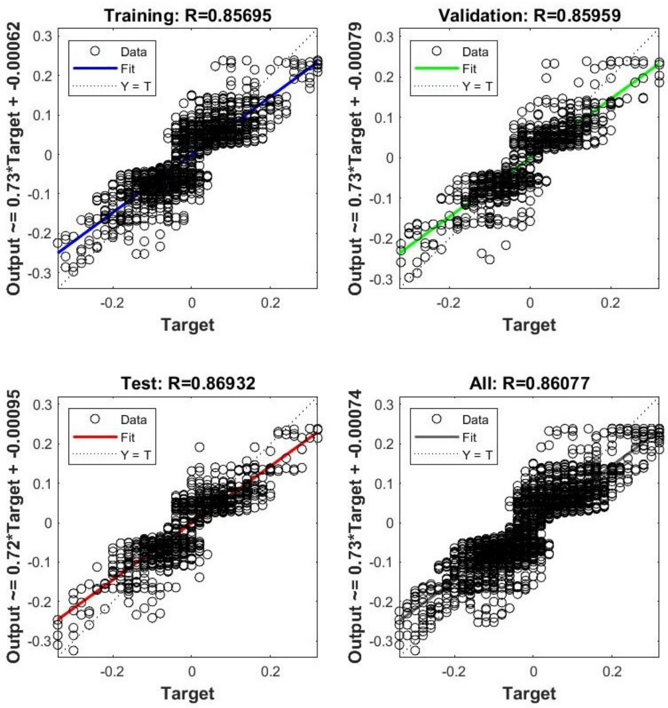

Fig. 7. Neural network regression

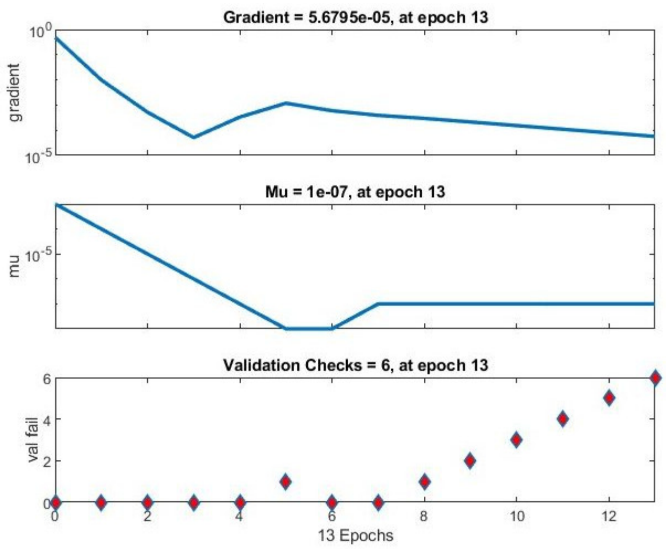

Fig. 8. Neural network training state

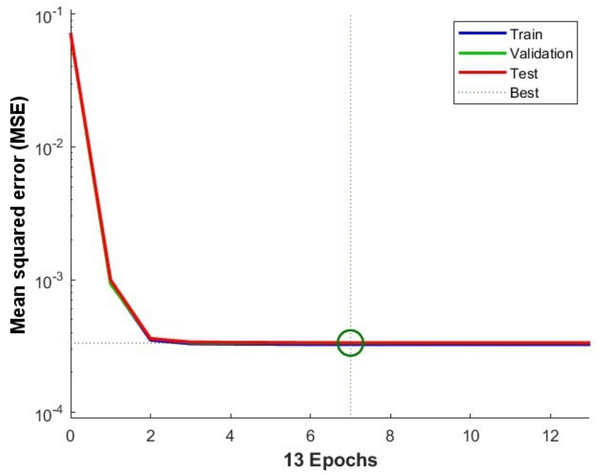

Fig. 9. Neural network training performance

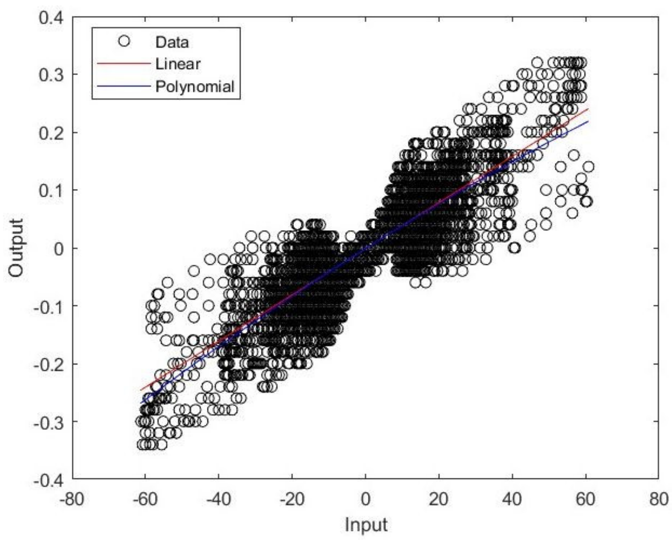

Fig. 10. Linear and polynomial regression results for integrated circuits supply

5. CONCLUSIONS

The use of neural networks as a tool based on artificial intelligence allows us to achieve much better results than using standard methods such as linear, nonlinear, or polynomial regression. The results presented in Table 2 show a significant increase in the accuracy of the results compared to real data samples. The computational complexity is much higher, but for such small data sets, the learning time of the neural network was a few seconds, which does not constitute any significant difficulty in its design. The disadvantage of the NN model is the difficult mathematical description resulting from the complexity of the layers. However, this is not a problem in the practical implementation of the learned NN for further use. It is possible to use the created structure and develop it for further applications. It would therefore be possible to create a complete model. The average value of the coefficient of determination for the neural network model in relation to all presented (according to Table 2) samples is 74.4%. Using the tools used so far allows us to obtain results that are worse by 37.6 percentage points for linear regression (average 36.8%), worse by 27 percentage points for polynomial regression (average 47.4%) and by 36 percentage points for nonlinear regression (average 38.4%). The best of the classical solutions is polynomial regression, however, the use of neural networks allows to achieve convergence that is higher by 27 percentage points. The most important conclusions resulting from the conducted research include:

- Due to the availability of libraries, neural networks are convenient and quick to implement.
- The training time of the neural network for a small data set does not differ from standard calculations.
- Neural networks make it possible to control more parameters.
- The use of artificial intelligence tools enables the optimization of calculations in terms of the expected accuracy.
- Increasing the number of neurons in the hidden layer speeds up the achievement of the result by reducing the number of epochs needed to end the simulation.
- The results obtained using NN are clearly better than other techniques (see the results in Table 2).

The results of the conducted research can help create a more accurate model of UAV using AI tools with a larger number of tested machines. The use of an innovative method of improving the accuracy of model mapping contributed to obtaining a more accurate representation of simulated data in relation to real ones. Thanks to this, it will not be necessary to conduct destructive tests on real equipment, but only simulations thanks to more accurate mapping.

The assumptions of developing models using artificial intelligence tools based on real measurements have been achieved. Using a neural network, a structure was learned that could be part of a later stage of work on an advanced model of unmanned aerial vehicles based on more real samples. The aim of this article was to show the performance of using AI models compared to classical regression methods, as shown in numbers. Further reproduction of this model will be possible after adding more input data for training neural networks or can be used "as is" by other researchers to improve by itself. In this model a small drone was used. If more complex equipment is necessary, it is also necessary to collect measurement data for this model. Of course, the NN-based AI model is universal and can be adopted to any type of UAV in terms of real measurement data samples.

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