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Investigation of the possibility of using artificial neural networks in the process of assessing the threat of lightning

Streszczenie. *W artykule została przedstawiona problematyka związana z możliwością wykorzystania sztucznej sieci neuronowej do przeprowadzenia klasyfikacji współczynników opisujących zagrożenie piorunowe. Przeanalizowano wybór najbardziej optymalnego rodzaju sieci neuronowej dla tego rodzaju zadania, a także kwestię danych wejściowych, które posłużą zarówno do uczenia sieci neuronowej, jak również stanowią podstawę do końcowej klasyfikacji. Na koniec wyciągnięte zostały wnioski oraz założenia niezbędne do praktycznej realizacji zadania. Praktyczna część zadania będzie stanowić kolejny etap rozważań. (**Badanie możliwości wykorzystania sztucznych sieci neuronowych w procesie oceny zagrożenia wyładowaniami atmosferycznymi**).*

Abstract. *The article presents issues related to the possibility of using an artificial neural network to classify factors describing the lightning hazard. It also analyzed the selection of the most optimal type of neural network for this type of task, as well asthe issue of input data, which both teach the neural network and form the basis for the final classification. Finally, the conclusions and assumptions necessary for the practical implementation of the task were drawn. The practical part of the task is planned as the following consideration stage.*

Słowa kluczowe: Matlab, Python, ryzyko szkód piorunowych, szacowanie ryzyka piorunowego, sztuczna sieć neuronowa, współczynnik położenia obiektu, współczynnik środowiskowy.
Keywords: Matlab, Python, lightning damage risk, lightning risk assessment, artificial neural network, structure location factor, environmental factor.

Introduction

Lightning risk is defined as the probable average annual loss to a facility due to lightning discharges, and the methodology for its assessment is described in the international standard IEC 62305 [1].This assessment is the basis for deciding on the need to use lightning protection and what additional protection measures for installations and technical devices against atmospheric surges are necessary. The risk value is influenced by many factors, such as the average annual density of ground discharges per km^2, the probability of causing damage by the affected lightning discharges or the average value of the occurring losses. When estimating the risk, one essential parameter is the structure location factorC_D and the environmental factor C_E because the values are often selected by the designer discretionarily. The consequence of such practices may be an erroneous decision to use or not to install lightning protection.

An improvement in estimating the lightning risk may be using artificial neural networks in the scope of correct classification of the values of these factors based on input data such as photos of the area withthe analyzed object. During machine learning, neural networks construct the user's needs models based on the training data set. This is done in such a way that the network user collecting representative data showing how the relationship of interest is expressed, and then running the network learning algorithm. This is done in such a way that the network user collecting representative data showing how the relationship of interest is expressed, and then running the network learning algorithm.This action is oriented towardautomatically creatingthe necessary data structure in memory. Based on a self-created data structure, the network performs all functions related to using the created model after completing the learning process.

Lightning risk estimation – example

According to the methodology for assessing the risk of lightning damage described in the standard [1], the value of this risk should be the basis for deciding if lightning protection is necessary and what kind of additional protection measures against atmospheric surges for installations and devices are necessary. When calculating the lightning risk, it is obvious to consider the parameters characterizing the object being analyzed. In particular, its location, equipment, environment and measures used to reduce direct and nearby lightning discharges effects are essential.

The purpose of the calculation is to estimate the risk R being the relative value of the probable average annual losses. An appropriate risk value should be determined for each type of loss in the facility. The sample calculations presented in the article were carried out for the case of an apartment block, for which there are typical risks associated with:

- loss of human life – R_1 with components R_A, R_B, R_U and R_V,
- loss of economic value – $R_4$is based on the economic value of the facility and its equipment.

A general equation expresses each risk component looks like (1):

$$R_x = N_x \cdot P_x \cdot L_x \tag{1}$$

where: N_x is the number of dangerous events per annum, P_x is the probability of damage to the structure, L_x is the consequent loss.

The number N_x depends on the density of groundflash density(N_g) and the physical characteristics of the object being protected, its surroundings, the number and type of connected lines and the electrical parameters of the ground. The probability of damage P_x depends on the characteristics of the object to be protected, the lines connected and used the protection measures. The loss of L_x depends on the facility's purpose, the presence of people, the type of public services, the value of the damaged goods and the means intended to limit the size of the losses. The estimated risk R should be compared with the tolerable value of the R_T specified in the standard [1].For loss of human life or permanent injury,R_T/year=10^{-5}. If the total risk $R \le R_T$, lightning protection is not necessary. If $R > R_T$, protection measures shall be applied to fulfil the condition$R \le R_T$concerningall risks to which the object and its equipment are exposed.

Analyzedfactors affecting the risk of lightning

The use of artificial neural networks, in particular, may concern two factors:

- structure location factorC_D,
- environmental factor C_E.

The object's relative location that minimizes the impact of the objects surroundingthe exposed location is considered using the structure's location factor C_D. The range of variability of its value is defined in the standard as follows [1]:

Table 1 Range of variation of C_D values

Relative location	C_D
Structure surrounded by higher objects	0,25
Object surrounded by objectsof the same height or smaller	0,5
Isolated structure: no other objects in the vicinity	1
Isolatedstructure on the top of a hill or knoll	2

The environment where the object is located is defined using the environmental factor C_E. The range of variability of its value is defined in the standard as follows[1]:

Table 2 Range of variation of C_E values.

Environment	C_E
Rural	1
Suburban	0,5
Urban	0,1
Urban with tall buildings (>20 m)	0,01

An example of a photographic comparison of the two environments is shown in Figure 1.

a)

b)

Figure 1 Photographic comparison of two environments: a) suburban environment (near Warsaw), b) urban environment (centre of Warsaw)[2].

As it can be seen, it is difficult at first sight to assess what kind of environment it is, and due to the five times difference in the value of the relevant factor, the error in estimating the risk can reach 500%.

Residential building – environmental and global characteristics of the facility

The exemplary analyzed object is a residentialbuilding. The basic parameters are presented in Table 3.

Table 3 Characteristic data of the example object.

Parameter	Value
Ground flash density, N_g *[1/km^2/year]*	4
Structure dimensions, *LxWxH [m]*	20x20x13
Collection area, A_D *[m^2]*	8298,36
Structure location factor, C_D *[-]*	0,25
Assumed lack of lightning protection, P_B *[-]*	1
Assumed no equalization connections, P_{EB} *[-]*	1
Environmental factor – case 1, C_{E1} *[-]*	0,5
Environmental factor – case 2, C_{E2} *[-]*	0,1

The location of the object described by the value of the factorC_E can be classified as problematic for a detailed assessment, which justifies conducting appropriate example calculations and taking up the topic.

Estimation of lightning risk values

Based on the adopted parameters, the lightning risk was calculated. The following tables show the risk values for two exemplary environmental factor values, respectively:

- $C_E = 0{,}5$ – *suburban environment (case 1)*

Table 4 Summary of partial risk values for the factor C_E = 0,5.

	Risk	Value
D1 –injury to living beings by electric shock	R_A	$8{,}30 \cdot 10^{-9}$
	R_U	$8{,}00 \cdot 10^{-9}$
D2 – physical damage	R_B	$8{,}30 \cdot 10^{-6}$
	R_V	$8{,}00 \cdot 10^{-6}$
Sum	R_1	$1{,}63 \cdot 10^{-5}$
Tolerated risk	$R_1 > R_T$	$R_T = 1 \cdot 10^{-5}$

- $C_E = 0{,}1$- *urban environment (case 2)*

Table 5 Summary of partial risk values for the factor C_E = 0,1.

	Risk	Value
D1 –injury to living beings by electric shock	R_A	$8{,}30 \cdot 10^{-9}$
	R_U	$1{,}60 \cdot 10^{-9}$
D2 – physical damage	R_B	$8{,}30 \cdot 10^{-6}$
	R_V	$1{,}60 \cdot 10^{-6}$
Sum	R_1	$9{,}91 \cdot 10^{-6}$
Tolerated risk	$R_1 < R_T$	$R_T = 1 \cdot 10^{-5}$

After comparingboth cases results, it can be concluded that lightning protection is required, or there is no need to use it depending on the stated value of the C_E. Many parameters influence the value of lightning risk, but the article is devoted to analyzing the factor's values: the structure'slocation and the environmental one. In the analyzed cases, whether the object is located in a suburban or urban environment was essential. It should be mentioned that a big challenge is to distinguish and properly select the factor value for these environments. The result of the presented calculations is the conclusion that in the case of a facility located in an urban environment, for the adopted parameters, there is no need to apply for lightning protection. This necessity exists in the case of the suburban environment.

The principle of operation of neural networks

The neural network is a very simplified model of the brain. It consists of a large number (from several hundred to tens of thousands) of information processing elements. These elements are called neurons, reached by a certain number of input signals (values) ($x_0 \dots x_n$). These are the values of raw data provided to the network from the outside as data for the calculations carried out. They can also be indirect signals from the outputs of other neurons in the network. Each value is introduced into the neuron by connecting with a specific weight (w_i). These weights correspond to the effectiveness of the synapse in a biological neuron. Each neuron also has a single threshold value that determines how strong it must be excited to ignite. In the neuron, the weighted sum of the inputs is calculated (the sum of the input signal values multiplied by the appropriate weighting factors), and then the threshold value is subtracted. The additional value obtained in this way determines the excitation of the neuron (*s*). The signal representing the cumulative excitation of the neuron is transformed by the predetermined activation function of the neuron (*f*). The value calculated by the activation function is ultimately the output value (output) of the neuron (y) [2].

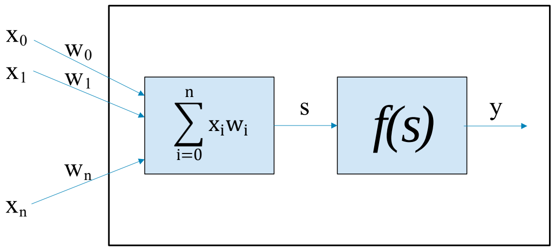

Figure 2The structure of an artificial neuron. x_0, x_1,..., x_n - input signals, w_0, w_1, ...,w_n - weighting factors, *s* - excitation neuron, *f(s)* - neuron activation function, *y* - output signal.

How the neurons connect and interact has created different types of networks. Each type of network is associated with an appropriate method of weighting. The most frequent types of networks are unidirectional single-layer networks (perceptrons), unidirectional multilayer networks (multilayer perceptrons), recursive or convolutional networks [3].

Figure 3 An example of a matrix transformation f(x)=x * [-1] as the function of a negative photo [4].

Types of neural networks

A perceptron consists of one neuron and is the simplest form of a neural network as it contains only two layers: input and output. A multilayer perceptron consists of an input layer, at least one hidden layer, and an output layer. Each neuron in one layer is connected to all neurons in adjacent layers.Although these networks are referred to as the multilayer perceptron (MLP), they are composed of sigmoid neurons, not perceptrons. In turn, recursive networks consist of input, hidden and output layers, supplemented with a feedback loop for at least one layer of neurons.They use either sequential or time series data in their work. They are commonly used to solve problems such as language translation, natural language processing and speech recognition. The third type of neural network isa convolutional network, the main element of which is a layer that uses convolution.The convolution operation is a matrix transformation of photo fragments, which aims to extract information about specific features of the image. A straightforward example might be a negative operation in which the image is multiplied by the matrix *[-1]* to invert the colours (Figure 3).

Compared to MLP networks, convolutional networks have an advantage in image recognition due to the speed of operation and information processing. The problems that may occur when using multilayer perceptrons are the need to train a large amount of data and the possible loss of information due to the adaptation of the image shape to the remaining data[3].

A proposal of a neural network solving the problem

In the lightning risk assessment process, the input layer parameters are photos of the rural, suburban or urban environment. The data can be obtained from aeronautical maps or photos with building's outlines (Figure 4) [1].

a)

b)

Figure 4 Comparison of possible photographic data sources: a) straight aerial photo, b) aerial photo with buildings outline [4].

Publicly available databases such as Google Maps or Geoportal can be considered topographic data sources. Helping by modern technology, it is possible to perform a drone raid equipped with a LIDAR camera over the analyzed object. Thanks to this, also numerical data are obtained, such as the height of the object and the surrounding infrastructure. Consequently, the advantage of this solution may be the simplification of the neural network structure.

The first stage of the neural network's operation is the stage in which it undergoes the learning process (

Figure 5).

Depending on the input data type, the network might be more or less complex (Figure 6).

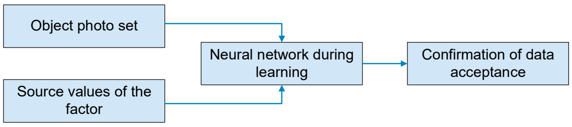

Figure 5 Algorithm of neural network operation in learning mode.

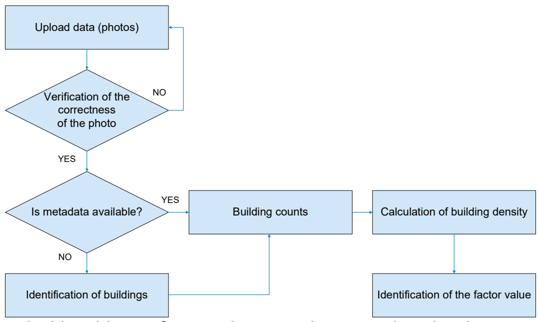

Figure 6 Algorithm of neural network operation in the operating mode.

Each image might be assigned a factor value or an intermediate parameter. The next step is the need to verify and detect input data in hidden layers. Verification includes checking areas such as the photo's resolution, size and scale.The detection is based on the assessment of the dimensions of the objects, such as height, width and length. The last task in hidden layers is counting objects to estimate the environment in which objects that require lightning protection are located.

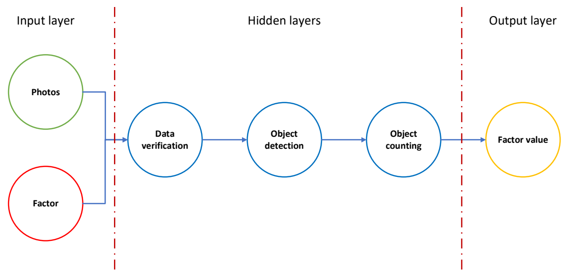

Figure 7 Schematic structure of a neural network resolving the problem.

The above activities generate the output data constituting the ready result represented by an appropriately selected value of the factor or the type of environment. It can potentially be an intermediate parameter, such as building density. Such information can be found in the output layer of the neural network shown in Figure 7.The best type of neural network used in this task may be convolutional neural networks. The rationale for this choice is the possibility of using this network for image recognition and computer vision. These networks use the rules of linear algebra, in particular matrix multiplication, to identify patterns in an image. The practical aspect of convolutional networks is the analysis of input data in the form of photos of environments or aerial maps, complete with a correctly selected value of the factors describing lightning hazards.

Summary and conclusions

1. The article describes the lightning risk estimation procedure and examples of calculation results for a residential building per the IEC 62305-2 standard.
2. Based on the performed comparative calculations, it can be concluded that:
    a) Lightning protection is necessary for the assumed value of $C_E = 0,5$ of the environmental factor. Itresults from the environment in which the analyzed facility is located, namely, a suburban environment.
    b) Selecting the values of the environmental factors and the object's location is discretionary, resulting in a wrong decision to apply or not to lightning protection.
    c) The improvement of the lightning risk assessment process is the use of an artificial neural network for the correct classification of the above-mentioned factor values.
3. The principle of operation of artificial neural networks was presented, as well as the idea of selecting and applying a neural network capable of achieving the assumed goal.
4. A diagram of the procedure in the lightning risk estimation process using an artificial neural network was presented.
5. The following part of the work is planned to perform a subject literature review and practical implementation of the network in Matlab or Python environment, along with an analysis of its operation optimization.
6. Automation of the lightning hazard assessment process with the use of a convolutional neural network created in the Matlab/Python environment should bring measurable benefits to the work of a lightning protection system designer.
7. The choice of Matlab or Python environments is dictated by their worldwiderecognized position and the large availability of libraries and documentation, which can be used to perform the task after supplementing the author's code.

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