

## Prognostic Models of *Panicum virgatum* L. Using Artificial Neural Networks

Vasyl Ivanovych Lopushniak<sup>1</sup>, Halyna Myhaylovna Hrytsuliak<sup>2</sup>,  
Anatoliy Viktorovych Bykin<sup>1</sup>, Nadia Petryvna Bordyuzha<sup>1</sup>,  
Larysa Oleksandryvna Semenko<sup>1</sup>, Myroslava Stepanivna Polutrenko<sup>1</sup>,  
Yulia Zinoviivna Kotsyubynska<sup>3</sup>

<sup>1</sup> National University of Life and Environmental Sciences of Ukraine, Heroiv Oborony Str.15, 03041, Kyiv, Ukraine

<sup>2</sup> Ivano-Frankivsk National Technical University of Oil and Gas, Karpatska Street, 15, 76000, Ivano-Frankivsk, Ukraine

<sup>3</sup> Ivano-Frankivsk National Medical University, Halytska Str. 2, 76018, Ivano-Frankivsk, Ukraine

\* Corresponding author's email: gritsulyaka@ukr.net

### ABSTRACT

The article shows the possibility of using modern methods of artificial intelligence to calculate the yield of biomass of crops according to the given set input data (fertilizer doses, agrochemical parameters of the soil, productivity). The study reflects the results of testing a model of a computer program of an artificial neural network, which allowed forecasting the yield of *Panicum virgatum* L. (Switchgrass) depending on the joint application of fertilizers mineral and precipitate. On the basis of the calculations, the obtained model of productivity of vegetative mass of switchgrass shows a high level of forecasting efficiency (up to 97%). According to the results of experimental studies, the use of sewage sludge at a doses of 20–40 t/ha provides a dry biomass yield of *Panicum virgatum* L. (Switchgrass) in the range of 13.1–20.3 t/ha, which is 3.4–7.2 t/ha more than in the option without fertilizer.

**Keywords:** switchgrass, productivity, biomass, sewage sludge, precipitate, artificial neural networks

### INTRODUCTION

In the energy balance of Ukraine, a large share of energy resources is accounted for by imported energy, but there are significant opportunities for environmentally friendly and inexpensive raw materials from renewable green energy sources, including phytomass of energy crops [Lesschen et al. 2012, Lopushnyak 2017, Lopushniak V.I. et al. 2021].

Achieving the maximum level of yield of energy crops at minimum cost is one of the most important goals and a key condition for the efficiency of agricultural energy production [Kharchenko et al. 2019, Mann 2012, Lopushniak, et al. 2021]. Predicting the productivity of agrophytocenoses on the basis of given parameters of agrochemical

indicators, agroclimatic conditions, as well as on the basis of experimental research using innovative tools for forecasting models can have a significant impact on the management decisions in agricultural business [Liu, et al. 2019, Tiginova 2012, Lopushniak V.I. et al. 2021]. Forecasts can be used by farmers to minimize risks and losses in production, as well as when planning the level of harvest and its resource provision [Iulian 2002, Karbivska 2020].

Modern approaches to yield forecasting use various models of mathematical origin and statistical tools. The use of modern methods of artificial intelligence for forecasting, namely artificial neural networks (ANN), has great prospects. Their application can simplify the models of mathematical origin (artificial neural networks), which

can be applied and used a large amount of data [Iulian 2002, Jha 2019, Karlik 2011]. An artificial neural network is a model computer program of mathematical origin that can be used to find common relationships between variable results and predicted results of the variables being studied, depending on the initial conditions. This model was used to calculate the biomass crops [Balan 2012, Rojas 2013, Haykin 2009, Specht 1990, Lopushniak V.I. et al. 2021].

The widespread attraction of non-traditional and renewable energy sources in the economy of any state is a promising direction of activating the economic environment and the development of the energy market. Production and energy consumption of renewable sources is rapidly developing in most European countries as well as in the United States. In Ukraine, non-traditional fuels occupy a small share in the energy balance, about 1.5% [Lesschen 2012, Tigonova 2015, Lopushnyak 2017]. Implementation of alternative energy sources, increase of volumes of renewable resources, including growing energy crops for the production of various types of biofuels, are relevant issues for the Ukrainian economy [Venkatesh 2012, David 2010, Eli-Chukwu 2019, Lopushniak V.I. et al. 2021].

As it is known, Ukraine belongs to energy-dependent countries: energy resources in the overwhelming majority are imported, which is reflected in the unceasing healthcare of non-renewable energy sources, reducing economic indicators of practically all industries [Elbersen 2001, Elbersen, 2013]. In view of this, the basic principles of state policy in the field of alternative types of fuel should be comprehensively promoting the development and rational use of non-traditional sources and types of energy raw materials for fuel production in order to save fuel and energy resources and reduce the Ukraine's dependence on their imports [Dagli 2012, Lesschen 2013, Gamayunova et al. 2020].

Ukraine has significant raw materials of biomass, biomass, which can be used for cost-effective and energy purposes [Jefferson 2012, Lopushniak V.I. et al. 2021], but experts believe [Kalynychenko 2018, Lopushnyak 2017] that to increase the share of renewable energy it is necessary to develop the cultivation of energy crops. Energy willow, poplar, miscanthus, *Panicum virgatum* L (Switchgrass), etc. are considered to be promising crops for growing for energy purposes

[Venkatesh 2012, Eli-Chukwu 2019, Lopushniak V.I. et al. 2021, Gamayunova et al. 2021].

Since the late 1980s in many countries, including the United States, Canada and some Scandinavian countries, switchgrass has been used as an energy crop for the production of solid and liquid biofuels [Elbersen 2001]. An important property of this culture is its ability to enrich the soil with a significant amount of organic matter (postharvest, root residues, leaf litter), which is easily mineralized in the soil environment, and can be useful for cultivating to improve the ecological condition of ecobiocenoses, soil degradation cover, etc. [David 2010, Eli-Chukwu 2019, Lesschen 2013, Lopushniak V.I. et al. 2021]. In Ukraine, *Panicum virgatum* L. (Switchgrass) is a relatively new crop that needs to be studied to determine the characteristics of its growth, development and formation of productivity depending on different ecological conditions of cultivation, in particular under different conditions of mineral nutrition. Considerable attention should be paid to the issues of fertilization of *Panicum virgatum* L. (Switchgrass), because – due to its ability to accumulate a significant amount of biomass – it removes a large amount of nutrients from the soil [Jefferson 2012, Karbivska 2020, Lopushniak et al. 2021].

The development of models of *Panicum virgatum* L. (Switchgrass) productivity on the basis of already performed field research and obtained experimental data remains an urgent issue, which will accelerate the introduction of culture into production and expand its growing areas.

At this stage of the agricultural sector development, modern information technologies play a significant role. Thus, on a large industrial scale, there are intelligent climate control systems for growing crops indoors [Eli-Chukwu 2019, Elbersen 2001, 2013, Iulian 2002, Lopushnyak 2017, Lopushniak, et al. 2021]; in addition, there are management systems for mineral nutrition during the cultivation of crops by hydroponic and aeroponic methods. Elements of artificial intelligence are successfully used in weed control, remote monitoring of soil cover indicators, precision agricultural production systems, quality control of technological operations, etc. [Jha 2019, Karlik 2011, Balan 2012]. Therefore, computer artificial neural networks can be used for predicting biomass or future productivity of crops, because their use minimizes the possibility of influencing the outcome of the human factor, helps to

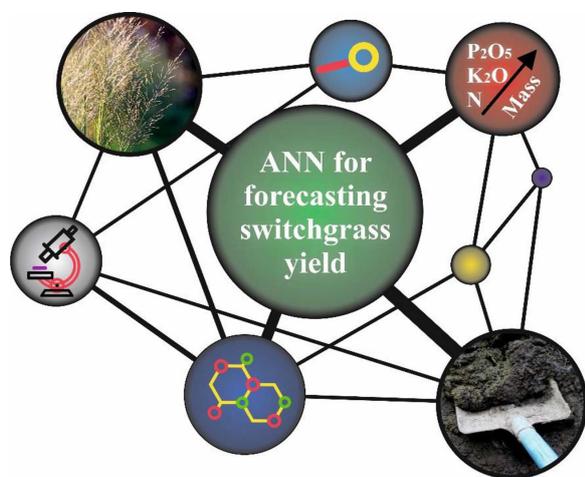
minimize errors and provides the ability to work 24/7 [Oludare Isaac Abiodun 2018, Rojas 2013, Lopushniak V.I., et al. 2021].

Formal neurons can combine in artificial networks in different ways and perform a variety of tasks [Dunets 2008, Lopushniak V.I. et al. 2021]. In our research, the task of the Artificial Neural Network was to predict the productivity of agrophytocenoses. The use of corrective models in predicting crop productivity allows reducing research periods as well as the resources used to obtain a correct representative result (Fig. 1).

The purpose of observations is to develop and forecast of agrophytocenoses of *Panicum virgatum* L. candlegrass (Switchgrass), using artificial neural networks to apply sewage sludge, on the basis of the obtained experimental data.

## MATERIALS AND METHODS

The study analyzed the stages of development of a model for predicting the yield of switchgrass using ANN. *Panicum virgatum* L. (Switchgrass), as an energy crop, has a number of advantages: it helps combat soil erosion, preserve natural conditions, improve soil structure and reduce the emissions of harmful greenhouse gases. The research was carried out on the territory of the experimental field of the plain part of the Ivano-Frankivsk region of Ukraine on podzols degraded soils within the Maidan settlement (Tsenzshiv station). The chemical composition of the soil and phytomass test samples with an accuracy of 1–10 ppm was determined by X-ray fluorescence analysis. The experiments were performed on an EXPERT 3L



**Figure 1.** Using ANN to form prognostic models of *Panicum virgatum* L. (Switchgrass) performance

analyzer, the main characteristic of which is the constant flow of helium into the channels of the collimator [Oyedotun 2018., Pugachev N.I. 2015, Lopushniak et al. 2021]. The data from experimental studies of agrochemical results of the soil were determined with an accuracy of 0.005%.

## Experiment options

Field studies include 8 variants of the experiment:

- 1) control (without fertilizers);
- 2)  $N_{60}P_{60}K_{60}$ ;
- 3)  $N_{90}P_{90}K_{90}$ ;
- 4) SS 20 t/ha +  $N_{50}P_{52}K_{74}$ ;
- 5) SS 30 t/ha +  $N_{30}P_{33}K_{66}$ ;
- 6) SS – 40 t/ha +  $N_{10}P_{14}K_{58}$ ;
- 7) compost (SS + straw (3: 1)) 20 t/ha +  $N_{50}P_{16}K_{67}$ ;
- 8) compost (SS + straw (3: 1)) 30 t/ha +  $N_{30}K_{55}$  [Lopushniak et al. 2021].

The area of the experimental plots is 35 m<sup>2</sup>, the repetition is three times. The biomass yield was determined by using the weight method at the experimental sites, while the dry matter content – with the method of drying at a temperature of +105°C to constant values [Oludare Isaac Abiodun 2018, Lopushniak, et al. 2021].

*Panicum virgatum* L. (Switchgrass) belongs to heat-loving multi-year plants with a well-developed root system, which increases the porosity of the soil, accumulation and maintenance of moisture in the soil, improving the agro-physic indicators [Elbersen 2013]. The root system develops better when subjected to the presence of damp conditions for several days. Under the low humidity of the upper layer of the soil, the development of plants will depend on the possibility of water and nutrients through the stems. Since the possibility of water and nutrients through the stems are insignificant, it limits. Another negative property of the culture is a tendency to take place through a thin stem and the possibility of breaking it [Venkatesh Bala 2012, David 2010, Elbersen 2013, Lopushniak, et al. 2021].

In terms of research, the cultivation of switchgrass involved the following technological operations: in the first decade of May, the crop was sown by hand at a distance of 50–55 cm in a row to a depth of 1.0–1.5 cm. Plants emerged after 25–30 days therefore, weeding between rows and destruction of weed seedlings was carried out periodically [Elbersen 2001, Lesschen 2012,

Lopushnyak 2017, Lopushniak V.I., et al. 2021]. In total, 4 interrow treatments were carried out at the sites with a frequency of 7–8 days. Interrow loosening improves the plant growing conditions, temperature, air, water, nutrient and microbiological soil regimes; prevent soil overheating [Kharchenko 2019, Elbersen 2001, Mininni, 2014, Lopushniak V.I., et al. 2021]. Increased gas exchange in the soil improves the activity of free-living nitrogen-fixing bacteria, beneficial microorganisms, nitrification processes, etc. After the candlegrass plants reached a height of 30–40 cm, no tillage was carried out.

### Research period 2016–2019

The winter months (December–January) are the period of harvesting phytomass of switchgrass. In this period, the moisture content of stems varies and is up to 17%. For this reason, the phytomass samples for laboratory research and harvesting were carried out in December [Mann 2012, Tigonova 2015, Lopushniak, et al. 2021]. Neural networks of various architectures, built using the program STATISTICA were used as the main mathematical model. The study was performed to predict the yield for growing switchgrass after application of fertilizers based on sewage sludge.

The input layer is a of neurons that can receive information, hidden layers are a of neurons that can process information, the output layer is a of neurons that produce the result. In general, currently artificial intelligence conditionally includes a model of mathematical form as a type of artificial neural networks (ANNs), which were actively developed by K. Bishop, A. Weig and others [Pugachev 2015, Lopushniak, et al. 2021]. Learning plays a key role in all these concepts. That is, in order for a computer program to function, it must be «taught.» The learning process itself can take place both on the basis of already known data and in the process of the program itself. Each of the artificial intelligence subtypes is applicable to certain tasks. Currently, the most researched and most promising in use are artificial neural networks. These models of mathematical origin are similar in their architecture and principle of operation to the human brain (hence the name) [Lesschen 2013, Haykin 2009, Tigonova 2015, Lopushniak et al. 2021]. Such models have the ability to perform a wide range of tasks, the main of which is forecasting. Unlike statistical

prediction methods, the Artificial Neural Network is not an accurate method in the sense that it works on the principle of a black box, i.e. the data is processed independently of the user, and the results are probabilistic [Oludare Isaac 2018, Lopushniak, et al. 2021]. This shortcoming is eliminated by the fact that modern artificial neural networks can predict the result with high probability levels that are close to 100 percent [Rojas 2013, Lopushniak, et al. 2021].

An artificial neural network consists of conditional «neurons», logical computing elements that can receive, process and transmit information. At the basic level, the association of neurons can be considered in layers: input, latent and output [Karlik 2011, Lopushniak, et al. 2021]. Figure 2 shows a schematic diagram of artificial neural network architecture. During the increase of gas exchange in the soil cover, the activity of nitrogen-fixing bacteria (free-living), microorganisms that benefit the soil, nitrification processes, etc. significantly increases, constituting a set of neurons that produce the result.

As already mentioned, the artificial neural network is a kind of computer program that operates a mathematical apparatus. Neurons in the network also operate on numbers that are usually in the range of [0,1] or [-1,1]. These limits are a kind of reaction of the neuron to the input signal. The neuron has two parameters, i.e. input and output. During operation, summary information from all neurons of the previous layer is entered into the input field. Next, the information is normalized using a special activation function  $f(x)$ , after which it goes to the output field [Dagli 2012, Dumitrache 2017, Lehtokangas 2000, Lopushniak, et al. 2021].

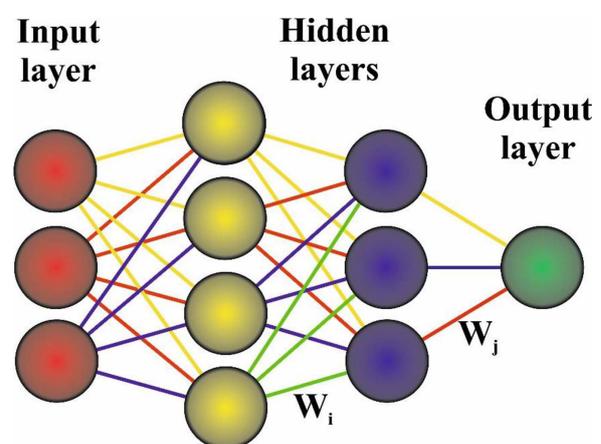


Figure 2. Structure of a neural network

As in the real brain, neurons are interconnected. By analogy, these connections are called synapses (Fig. 2,  $W_i$ ,  $W_j$ ). The synapse has a clear numerical value, i.e. weight of synapse [Dagli 2012, Dumitrache 2017, Lehtokangas 2000, Lopushniak, et al. 2021]. Information change (information processing) occurs due to synapses. The example (Fig. 3) shows how the mass of the synapse affects the color. As can be seen from the figure, each color contributes to the result and the processing of the input data will result in a certain result, in which the most main role will be played by the synapse with the greatest mass. In fact, the network of neurons that are connected by synapses allows making decisions. Of course, the complexity of the problem directly correlates with the number of neurons to solve it.

In addition to synapses, there is a concept of neuron activation functions in the system [Iulian 2002, Jha 2019, Karlik 2011]. This function that allows decryption of the warehouse system as numbers belonging to a range of values, for example  $[0,1; -1,1]$ . During operation, the activation function compares the input weights with some threshold. If the amount exceeds the range, the investigated element gives a signal; on the other hand, the signal is not investigated (or a braking signal is generated) [Karlik 2011, Liu 2018, Lopushniak 2020, Mann 2012, Lopushniak, et al. 2021].

For the correct operation of the Artificial Neural Network, training is required, i.e. it is

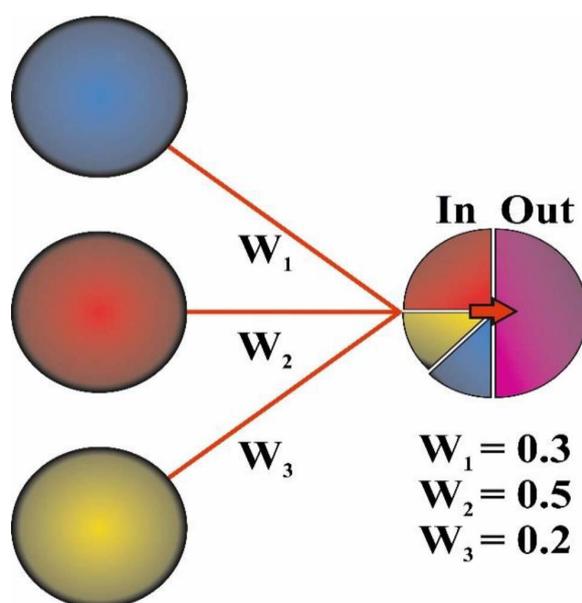


Figure 3. The result of neural data processing depends on the weight of the synapses

necessary to set the scales of the synapses in the system, which will correspond to this particular task. Network training requires data that is similar to what the network will process during operation. In this case, there must be both input data and result. The data can be both numeric and non-numeric. If the data are non-numerical they are structured according to certain categories [Dagli 2012, Dumitrache 2017, Karlik 2011, Lopushniak, et al. 2021].

Therefore, it is possible to create artificial neural networks in different ways. Thus, when creating neural networks for large enterprises or organizations, this is done by specially trained specialists – programmers. However, for small research purposes, one can use equipment that is available to everyone; the power of modern personal computers allows handling quite complex tasks. In order to create neural networks, ready-made solutions that target different levels of users can be used [Balan 2018, Rojas 2013, Lopushniak V. I., et al. 2021].

The studies presented in this paper were performed using the STATISTICA licensed software package [Jha 2019, Rojas 2013, Lopushniak V.I., et al. 2021]. This program allows successfully creating neural networks of various types and architectures. Its main advantage is the ease of use with all the necessary professional opportunities. It is also important that after learning Artificial Neural Networks, they can be exported in the form of program code or even conduct research on new data and instantly get the result directly in the program.

## RESULTS AND DISCUSSION

The results of field experiments to study the effect of mineral fertilizers in conjunction with different rates of sewage sludge on the formation of biomass productivity of switchgrass served as input data for the development of prognostic models of forecasting plant biomass using a computer program called artificial neural networks. Table 1 shows the study area for one of the groups. The data in the table shows the doses of fertilizers and the corresponding biomass yield. Where, N,  $P_2O_5$ ,  $K_2O$  – made with mineral fertilizers N,  $P_2O_5$ ,  $K_2O$ ; N \*,  $P_2O_5$  \*,  $K_2O$  \* – applied with organic fertilizers (composts), Mass – mass of candlegrass (t/ha). The total amount of fertilizers applied was 270 kg/ha of active substance. Options 3–8

**Table 1.** Experimental variants

Variants	N	P <sub>2</sub> O <sub>5</sub>	K <sub>2</sub> O	N*	P <sub>2</sub> O <sub>5</sub> *	K <sub>2</sub> O*	Mass
1. control (without fertilizers)	0	0	0	0	0	0	13,1
N <sub>60</sub> P <sub>60</sub> K <sub>60</sub>	60	60	60	0	0	0	15,0
N <sub>90</sub> P <sub>90</sub> K <sub>90</sub>	90	90	90	0	0	0	17,5
4. SS 20 t/ha + N <sub>50</sub> P <sub>52</sub> K <sub>74</sub>	50	52	74	40	28	16	16,5
SS -30 τ/ra + N <sub>30</sub> P <sub>33</sub> K <sub>66</sub>	30	33	66	60	47	24	18,4
SS – 40 τ/ra + N <sub>10</sub> P <sub>14</sub> K <sub>58</sub>	10	14	58	80	66	32	20,3
compost (SS + straw (3: 1)) 20 t/ha + N <sub>50</sub> P <sub>16</sub> K <sub>67</sub>	50	16	67	30	64	23	18,0
compost (SS + straw (3: 1)) – 30 τ/ra + N <sub>30</sub> K <sub>55</sub>	30	0	55	60	90	35	18,9

are balanced by elements – NPK [Iulian 2002, Lesschen 2013, Lopushniak et al. 2021].

A statistical evaluation of the inputs used as initial results for ANN (Table 2). The table shows the main values, the mathematical deviation of the values of these fertilizers of all studied samples [Lopushnyak et al. 2021].

Neural networks carried out training according to the principle of strategy of the ANS model. The strategy of choice of randoms was selected 5 random with a relative percentage ratio: educational (0,70) – control (0,15) – test (0,15) [Rojas 2013, Lopushniak, et al. 2021]. 20 networks were trained during the research. Activation functions for outgoing neurons have chosen Identity, Tanh. Identity, Tanh, and Exponential were chosen as activation functions for hidden neurons. Depending on the complexity of the problem, one can select options, but they can also change frequently [Rojas 2013, Specht 1990]. The parameters for

constructing a typical neural network are selected based on the results of experimental field experiments [Lopushniak, et al. 2021].

According to the properly obtained and structured models for learning, the construction of artificial neural networks can be an effective helper that can successfully predict the productivity of agrophytocenoses. The only disadvantage of this method is the need for large amounts of data to train neural networks [Rojas 2013, Lopushniak, et al. 2021]. As a result of training, 5 so-called ANN models were obtained, which were characterized by different impact indicators. In this example, biomass productivity is the percentage of correct forecasting in the sample (from 0 to 100%) [Rojas 2013, Lopushniak, et al. 2021]. Figure. 4 shows the ANN obtained after graduation and the network with maximum performance (MLP 6–10–1: 6 input, 10 hidden, 1 output neurons). Each trained network corresponds to its

**Table 2.** Statistical evaluation of input data

Samples	Data statistics (Switchgrass in WorkbookG)						
	N	P <sub>2</sub> O <sub>5</sub>	K <sub>2</sub> O	N*	P <sub>2</sub> O <sub>5</sub> *	K <sub>2</sub> O*	Mass
Minimum (Train)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	14.90000
Maximum (Train)	90.00000	90.00000	90.00000	80.00000	90.00000	35.00000	20.00000
Mean (Train)	40.00000	30.96875	58.18750	33.43750	39.03125	16.81250	17.61875
Standard deviation (Train)	24.88684	28.92870	24.32102	27.77901	33.66005	13.53237	1.50428
Minimum (Test)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	15.80000
Maximum (Test)	90.00000	90.00000	90.00000	80.00000	66.00000	32.00000	18.10000
Mean (Test)	37.50000	39.00000	55.50000	30.00000	23.50000	12.00000	17.02500
Standard deviation (Test)	41.12988	40.48045	39.23859	38.29708	31.25700	15.31883	0.94648
Minimum (Validation)	10.00000	14.00000	58.00000	0.00000	0.00000	0.00000	16.90000
Maximum (Validation)	90.00000	90.00000	90.00000	80.00000	66.00000	32.00000	18.30000
Mean (Validation)	42.50000	44.50000	66.50000	40.00000	33.00000	16.00000	17.70000
Standard deviation (Validation)	38.40573	38.06573	41.12177	40.00000	33.12602	16.00000	1.79072
Minimum (Overall)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	14.90000
Maximum (Overall)	90.00000	90.00000	90.00000	80.00000	90.00000	35.00000	20.00000
Mean (Overall)	40.00000	33.12500	58.75000	33.75000	36.87500	16.25000	17.56750
Standard deviation (Overall)	27.26884	30.31221	24.80049	29.93047	33.33373	13.85594	1.39309

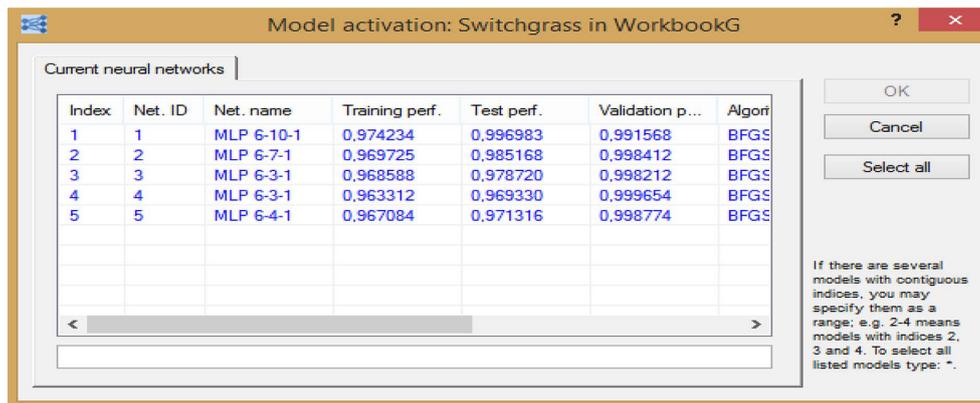


Figure 4. Characteristics of the productivity of the received neural networks

architecture and the value of its performance (ie the percentage of prediction in the training and validation subsamples). All trained networks have high performance of the built model. Among the ANN data, the network with the highest performance was noted (MLP 6–10–1).

The sensitivity analysis (Sensitivity Analysis) of the variables included in the model is also important. Table 3 shows the results of sensitivity assessment.

The numerical values in Table 3 show how many times the model error will increase if the corresponding variable is removed from it. According to the obtained results, the largest contribution to the learning of the obtained artificial neural network is made by the variable  $P_2O_5^*$  ( $P_2O_5$  SS + straw) [Lopushniak et al. 2021].

The result was ANN, which gives good prediction results on a test sample. In order to verify the correct operation of the obtained neural network, it is necessary to conduct research on independent data. The STATISTICA software package allows checking new data directly in the resulting network window. Thus, for example, taking – N – 8,  $P_2O_5$  – 12,  $K_2O$  – 50,  $N^*$  – 82,  $P_2O_5^*$  – 68,  $K_2O$  – 32 the neural network predicted the resulting mass of switchgrass (*Panicum Virgatum* L.) at 20.3 t/ha. This prediction agrees well with the experimental data and shows the actual valid performance (relationship between the data) of the network [Lopushniak et al. 2021].

On the basis of the new data table. 4., it is possible to estimate that the network predicts

productivity accurately. Since the model indicators of variables (fertilizers) do not differ significantly from the experimental ones, the forecast for biomass productivity should be close in value. If the network showed data on the productivity of biomass with a large deviation (for this example, say, 23.8), then, accordingly, it works effectively in the test sample, but with the new data, its work would be unsatisfactory [Lopushniak et al. 2021]. Figure 5 shows the relationship between the experimental data (target axis) and the calculated data (output axis) in the test sample.

The correlation dependence of mass predict (expected data) on mass Target (experimental data) can be described by the following multiple regression equation:

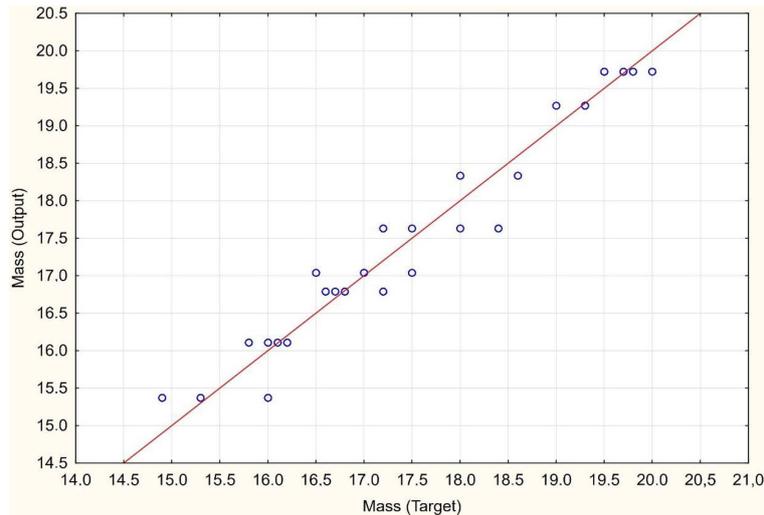
$$y = 0.9167 + 0.9476 x + 1.2354y \quad (1)$$

where:  $y$  is the mass predict (expected data);  
 $x$  – mass Target (experimental data).

The multiple coefficient of determination ( $R^2 = 0.795$ ) experimental data indicate a high correlation [Lopushniak, et al. 2021]. In the Figure 5, the blue dots show the relationship between the studied and calculated data, and the red line indicates a complete match between the forecast and experimental data. As it can be seen, the predicted results are close to the results obtained experimentally with a small deviation, which confirms the high quality of the prognostic model.

Table 3. Analysis of the sensitivity of the variables included in the model

Networks	Sensitivity analysis (Switchgrass) Samples: Train					
	$P_2O_5^*$	$K_2O$	$P_2O_5$	N	$N^*$	$K_2O^*$
1.MLP 6–10–1	48.90945	3.810826	3.370539	2.304169	1.972456	1.349814



**Figure 5.** Relationship between experimental and calculated switching biomass productivity data

**Table 4.** Sensitivity analysis of variables that are not included in the model

Networks	N	P <sub>2</sub> O <sub>5</sub>	K <sub>2</sub> O	N*	P <sub>2</sub> O <sub>5</sub> *	K <sub>2</sub> O*	Mass
Experiment	10	14	58	80	66	32	20.3
Forecast	8	12	50	82	68	32	20.3

## CONCLUSIONS

On the basis of the performed studies, the possibility of applying a computer program of artificial neural networks to prevent forecasting the productivity of agrophytocenoses and determining the amount of biomass of energy crops according to the given input parameters, in particular: fertilizer application rates, agrochemical indicators of soil, was proven. The main advantage of this method of predicting the productivity of energy crops is the ease of execution of the available IT tools and instant yield of the most accurate result directly in the program.

The developed prognostic model of switchgrass productivity with application of typical artificial neural networks on the basis of results of experimental studies provides high accuracy of forecasting which closely correlates with the indicators of the previously carried out field experiments. The predicted results are close in values with the indicators obtained experimentally, which confirms the high quality of the model.

Construction of artificial neural networks is a well-functioning, fast and time-consuming method of predicting the yield of cultivated plants in general and candlegrass in particular. With properly trained and structured training data, this approach can be an effective helper that

can successfully predict the productivity of agrophytocenoses and reduce the risks of agricultural production.

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