ECOLOGICAL ENGINEERING & ENVIRONMENTAL TECHNOLOGY

Ecological Engineering & Environmental Technology 2021, 22(3), 11–19
https://doi.org/10.12912/27197050/134867
ISSN 2719-7050, License CC-BY 4.0

Received: 2021.03.02
Accepted: 2021.03.22
Published: 2021.04.06

Forecasting the Productivity of the Agrophytocenoses of the Miscanthus Giganteus for the Fertilization Based on the Wastewater Sedimentation Using Artificial Neural Networks

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ABSTRACT
The observations of plant development were carried out for three years. The most desirable period for harvesting the miscanthus is December. During this period, the humidity of the stems decreases to 17%. For this reason, the samples for laboratory tests were taken in December. According to the obtained research data, the sewage sludge used is characterized by the following indicators: humidity – 76%, ash content – 5%, nitrogen – 0.66%, P_2O_5 – 2.51%, K_2O v 2.16%. In this study, a mathematical model which allowed predicting the yield of the miscanthus at given levels, with the introduction of the mineral and organic (sewage sludge) fertilizers was successfully implemented. According to the performed research, the application of a sewage sludge in norm of 20–40 t/ha promotes the productivity of the power cultures (the miscanthus) within 24.5–27.1 t/ha, thus increasing productivity on 2.3–5.1 t/ha, compared with control.

Keywords: miscanthus, bioenergy, productivity, sewage sludge, artificial neural networks, artificial intelligence.

INTRODUCTION

The energy needs of the modern world are too great, and their scale has approached a state where not only economic but also natural factors limit the involvement of the traditional energy resources. Already at the beginning of the 21st century, up to 1 billion tons of the conventional fuel of the vegetable mass have been used for the energy purposes, which is equivalent to 25% of the world oil production (Vambol 2018, Tryboi 2018, Rojas 2013, Haykin 2009). The energy crops are an effective way to solve the problems with the long-term supply of the raw materials. According to the estimates of the Bioenergy Association of Ukraine, the potential of the bioenergy is 21 million tons of the energy, including about a 7 million tons of the energy crops on 2 million hectares of the land (Vambol 2018, Specht 1990, Zheliezna 2014).

In the developed countries of the world (USA, China, Germany, Great Britain, Denmark, Australia, Spain, Poland, etc.) the production and use of the energy crops as biofuels is actively developing. Various crops (corn, rapeseed, winter wheat, sunflower, willow, poplar, etc.) are used as sources of the organic biomass. One of the non-traditional energy crops that has been of interest to researchers in the last two decades is the miscanthus (Nussbaumer 2004, Wagner 2017, Zheliezna 2014, Alexopoulou 2012).

The miscanthus, which is huge in terms of the dry biomass yield, solar energy efficiency and environmentally friendly cultivation technology, has certain advantages over other energy crops. In the available professional and popular science literature, the miscanthus is positioned as a crop capable of providing high yields of the biomass – about 20–30 tons of the dry matter per hectare

(Fantozzi 2010, Alexopoulou 2012, Cherubini 2011, Heller 2003). It is not particularly demanding in terms of soil fertility, so it is suitable for growing in poor lands, where traditional crops cannot bring good yields. It is similar to appearance to corn or reeds. This is a perennial plant, which, having seeds, reproduces exclusively by parts of the rhizomes – rice (Alexopoulou 2010, Cherubini and Strømman 2011, Heller 2013, Fantozzi 2010, Lopushniak 2020a).

The degraded soils, due to their characteristics, are optimal for growing energy plantations. They are well supplied with moisture and nitrogen, allowing plants to accumulate a fairly substantial biomass with moderate application of the mineral fertilizers. In addition, the cultivation of the continuous crops on contaminated, degraded soils is an important factor in the ecologically balanced use of these lands (Lopushniak 2018b, Karlik 2011, Felten 2012).

The purpose of the research is to develop and evaluate a methodology for predicting the productivity of agrophytocenoses of the giant miscanthus with the introduction of the sewage sludge using artificial neural networks.

MATERIALS AND METHODS

The research was carried out in the Tysmenytsia district of the Ivano-Frankivsk region on sod-podzolic degraded soils on the territory of the Maidan settlement (Tsenzhiv station). The studies of the chemical composition of the experimental samples were performed by X-ray fluorescence analysis. The method is based on the analysis of the fluorescence spectra of the elements emitted during the adsorption of the high-energy radiation. The method allows obtaining the data on the chemical composition of the substance in a wide range with an accuracy of 1–10 ppm. The experiments were performed on a precision analyzer EXPERT 3L with a constant supply of the helium into the channels of the collimator. These studies allowed controlling the agrochemical parameters of the soils with an accuracy of 0.005% (Calderon 2017, Cherubini 2011).

Experiment options

1. control; 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 in the ratio 3: 1) 20 t/ha + $N_{50}P_{16}K_{67}$; 8. compost (SS + straw in the ratio 3: 1) 30 t/ha + $N_{30}K_{55}$.

Options 3–8 are balanced by the introduction of the main elements of the mineral nutrition – NPK (Lopushniak 2020).

The miscanthus was planted by hand according to the scheme 50 x 70 cm. The width of the experimental plot is 5.0 m; length – 7.0 m; accounting area – 35.0 m^2. The total area of the experimental plot is 63 m^2. The placement of the plots in three repetitions is systematic. All the work, except for soil preparation, was carried out manually. The rhizomes with 5 - 6 growth buds were used for better rooting. The depth of the rhizome making is from 12 cm (Dagl, 2012).

Usually, in the first years, the plant forms a strong root system. The lines do not close. In the first years of the growing season at the beginning of the regrowth at plant heights of 15–20 cm loosening between rows was carried out. The plant is resistant to frost, due to a significant increase in rhizome and the number of the aboveground shoots, the continuous herbage is formed. During this period, the miscanthus is very competitive with weeds and does not require row spacing (Felten 2012., Grytsulyak 2016, Dondini 2009).

The observations of plant development were carried out for three years. The most desirable period for harvesting the miscanthus is December. During this period, the humidity of the stems decreases to 17%. For this reason, the samples for laboratory tests were taken in December (Rojas 2013). According to the obtained research data, the sewage sludge we used is characterized by the following indicators: humidity – 76%, ash content – 5%, nitrogen – 0.66%, P_2O_5 – 2.51%, K_2O – 2.16%.

Various approaches and methods are currently used to predict crop yields. These are mainly methods based on statistical processing of the data obtained in previous years and the subsequent approximation of these data to a certain mathematical model (Haykin 2009). Modern information technology makes it possible to solve this problem using elements of the artificial search, namely artificial neural networks. An artificial neural network (ANN) is a mathematical model that is similar in structure to the human nervous system. Like humans, ANN can learn and generalize knowledge. That is why ANN is referred to as artificial intelligence. ANN is widely used in all fields of the science. There are many different types of ANNs that focus on the specific tasks (Rojas 2013).

In general, ANN is a system of the interconnected and interacting processors (neurons). A neuron (the basic element of ANN) is a simple computing processor that can receive, process, and transmit information. When a large number of the neurons are combined into a single network, the system can solve non-trivial problems.

The neurons in ANN are combined into layers (Fig. 1) – the input layer (the set of neurons that receive information), *n* hidden layers (the set of the neurons that process information), and the output layer (neurons which output the result).

During the operation, the neurons operate on numbers. Usually, these numbers are in the range [0, 1] or [-1, 1]. Each neuron has two parameters: input data and output data. The input data field contains the summary information from all the neurons in the previous layer. After receiving the data, the information is normalized using the activation function f (x), after which it enters the output data field. It should be noted that for the input layer of the neurons, the input information is equal to the output (input = output).

All the neurons are connected to a network by synapses (Fig. 2, Wi, Wj). A synapse is a connection between two neurons that is characterized by the weight of the synapse [14].

Due to the weight of the synapse, the input information changes during the transmission from one neuron to another. Figure 2 shows how the weight of the synapse can change the data on the example of the colors. During the processing of the input data, a result will be obtained in which the most important role will be played by the synapse with the greatest weight. The totality of all weights of the neuronal synapses allows the system to make decisions. Depending on the complexity of the task, the number of the neurons and layers can vary greatly.

Another important element of the neural network is the activation function ([15]) – a function that normalizes the input data (i.e. a function that allows interpreting the data in the form of the numbers belonging to the range [0, 1]). In the activation function to determine the output data, the total amount of the input data and weights

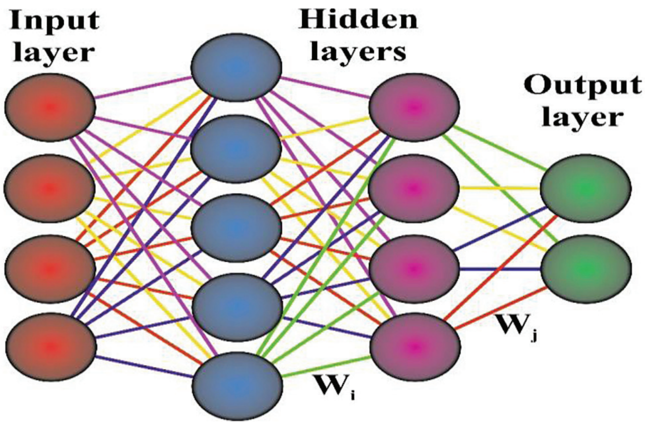

Figure 1. The structure of a neural network

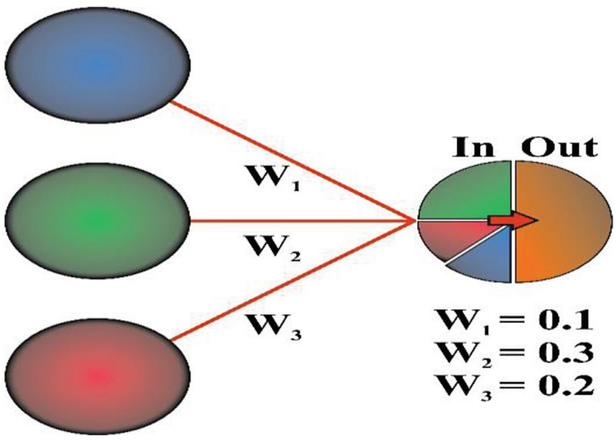

Figure 2. The dependence of the result of the neuron data processing on the weight of the synapses

is compared with some threshold. If the sum is greater than the threshold value, the processing element generates a signal. Otherwise, the signal is not generated (or a brake signal is generated) (Karlik and Olgac 2011). The sigmoid function is the most often used in practice (Fig. 3). An important feature of the sigmoid is the continuity of the functions and their derivatives. In the case of the use of non-numerical data, they are structured on categories (Table 1).

The power of the modern computers allows handling quite complex tasks, even on non-specialized devices. The interested parties can create and teach ANNs on regular computers using the publicly available software. There are a large number of the software packages for working with ANN (Dagli, C. H. (Ed.). 2012). Most of them are aimed at an experienced user who has programming skills.

Among the software with a low entry threshold, one can be including STATISTICA (Karlik and Olgac 2011). This program allows quickly building ANN of different architecture and complexity. It is also important that after learning ANN in this program, one can immediately conduct research on new data and obtain results instantly.

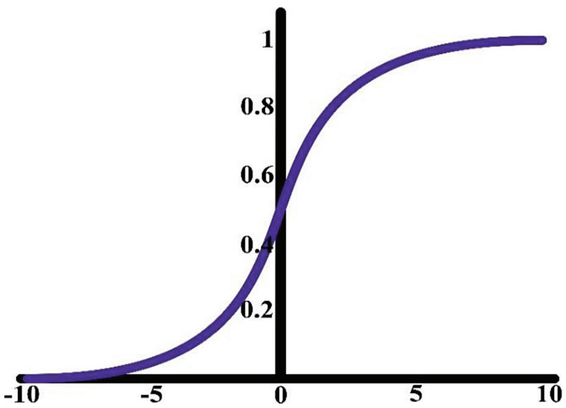

Figure 3. The nonlinear activation function that approximates the minimum and maximum values in asymptotes

RESULTS AND DISCUSSION

The STATISTICA program was used to build and train artificial neural networks. The input data were the norms of the mineral fertilizers, sewage sludge and compost based on them, as well as the obtained result of the raw mass of the miscanthus.

Table 2 shows a diagram of the experiment for one of the groups of the sites. The data presented in the table represent the amount of the application of a particular type of the fertilizer and the corresponding yield. Thus, N, P_2O_5, K_2O – applied with the mineral fertilizers N + SS, P_2O_5 + SS, K_2O + SS – applied with the organic fertilizers (sewage sludge + straw), Mass – the mass of the miscanthus (t/ha). Under Manure, respectively, it is meant a set of the fertilizers of the studied options. From each variant, 5 independent samples were taken accordingly for more exact mathematical processing. Accordingly, we obtained 40 results (Table 2). The total amount of the fertilizers was: For 1 – without fertilizers, 2 – 180, all others – 280 – the sum of the basic agrochemical indicators. A general view of the experimental data used for ANN is shown in Figure 4.

Table 3 shows the basic statistical evaluation of the data that served as input for the training of ANN. This study is performed to estimate, if necessary, the average value of the variables and their standard deviation. The training of the neural networks was carried out using the strategy of building the ANS model (automated neural network) (Table 3).

The training of the neural networks was conducted using the strategy of building the ANS model (automated neural network). By the strategy of the selection of the subsamples, 5 random subsamples were chosen with a relative percentage: educational (70%) – control (15%) – test (15%). Logistic, Tanh (logistic and hyperbolic functions) were selected as activation functions

Table 1. The example of an input table for ANN

N	Data				Result
1	$Data_{11}$	$Data_{12}$	…	$Data_{1i}$	$Result_1$
2	$Data_{21}$	$Data_{22}$	…	$Data_{2i}$	$Result_1$
3	$Data_{31}$	$Data_{32}$	…	$Data_{3i}$	$Result_2$
…	…	…	…	…	…
j	$Data_{j1}$	$Data_{j2}$	…	$Data_{ji}$	$Result_1$

Note: The number in order corresponds to a certain rate of the fertilizer. The $Data_{ji}$ – data recorded in a particular case and grouped by the appropriate options.

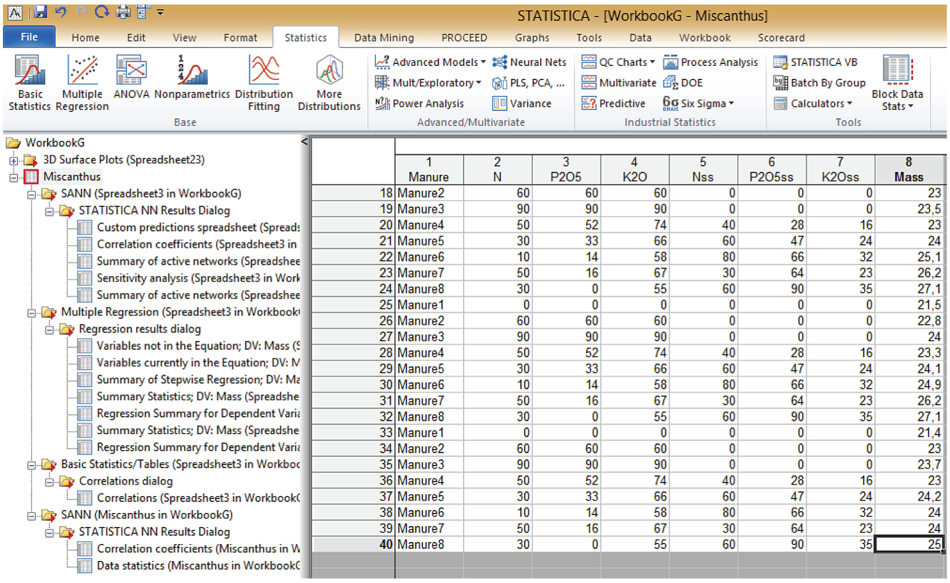

Figure 4. The experimental data for ANN training (general view)

Table 2. The experimental scheme (one of the groups of the sites)

Manure	N	P_2O_5	K_2O	N+SS	P_2O_5SS	K_2O+SS	Mass
Manure1	0	0	0	0	0	0	22.1
Manure2	60	60	60	0	0	0	23
Manure3	90	90	90	0	0	0	23.8
Manure4	50	52	74	40	28	16	23.5
Manure5	30	33	66	60	47	24	24.4
Manure6	10	14	58	80	66	32	25.1
Manure7	50	16	67	30	64	23	26
Manure8	30	0	55	60	90	35	26.9

Table 3. The statistical evaluation of the input data (minimum and maximum value, average value and standard deviation for each of the samples)

Samples	Data statistics (Miscanthus in WorkbookG)						
	N input	P_2O_5 input	K_2O input	N_{ss} input	P_2O_{5ss} input	K_2O_{ss} input	Mass target
Minimum (train)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	21.40000
Maximum (train)	90.00000	90.00000	90.00000	80.00000	90.00000	35.00000	27.10000
Mean (train)	41.07143	33.07143	59.35714	33.92857	38.35714	16.71429	24.15357
Standard deviation (train)	25.28933	30.06650	23.33050	28.58895	34.57489	13.96519	1.60081
Minimum (test)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	21.50000
Maximum (test)	90.00000	90.00000	90.00000	60.00000	64.00000	24.00000	26.20000
Mean (test)	36.66667	25.83333	48.33333	20.00000	29.16667	11.66667	24.00000
Standard deviation (test)	34.44803	33.75451	38.51580	24.49490	32.54791	12.78541	1.91520
Minimum (validation)	10.00000	14.00000	58.00000	0.00000	0.00000	0.00000	23.00000
Maximum (validation)	90.00000	90.00000	90.00000	80.00000	66.00000	32.00000	25.10000
Mean (validation)	38.33333	40.66667	66.33333	46.66667	37.66667	18.66667	24.16667
Standard deviation (validation)	33.51617	32.74039	32.02707	39.66527	32.37180	15.86611	1.19471
Minimum (overall)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	21.40000
Maximum (overall)	90.00000	90.00000	90.00000	80.00000	90.00000	35.00000	27.10000
Mean (overall)	40.00000	33.12500	58.75000	33.75000	36.87500	16.25000	24.13250
Standard deviation (overall)	27.26884	30.31221	24.80049	29.93047	33.33373	13.85594	1.53863

for the source neurons. The selected activation functions for hidden neurons were Logistic, Tanh and Exponential (logistic, hyperbolic, and exponential). Moreover, the number of the hidden neurons was selected as input parameters - from 3 to 20. The decaying regularization of the weight of the neurons (weight decay) – from 0.001 to 0.01 (for hidden layers) was set. The number of networks trained is 20.

These parameters were selected experimentally. In general, the parameters are selected depending on the complexity of the problem and can vary widely (http://neuralnetworksanddeeplearning.com/). After the learning ANN, 5 ANN models were obtained, which had different performance indicators. The productivity in this case is the percentage of the correct prediction in the test sample (from 0 to 100%). Among the obtained ANNs, a network with optimal performance was selected. Figure 5 shows the ANN obtained after training and the network with optimal performance (network No. 5). MLP 6-3-1 (6 input, 3 hidden, 1 output neurons).

It is worth noting that the forecast results are often not satisfactory; then, one can improve the result by going to the CNN model, where the refinement input can be set (namely – RBF network type – radial basis function, number of the training networks, number of the hidden neurons and number of the epochs). Such operations can be performed until the test performance and learning performance will suit us, according to the performance data.

The sensitivity analysis of the variables included in the model is also important. In table 4, it is shown the results of the sensitivity assessment.

According to the obtained results, the largest contribution to the model is made by the variable P_2O_5 + SS (option 8). In view of this, in further research and change of the settings, it is also necessary to pay special attention to this option (Compost (SS + straw (3: 1)) - 30 t/ha + $N_{30}K_{55}$) fertilization of the energy crops.

The result was ANN, which gives good prediction results on a test sample. The software package allows checking other data, i.e. entering other options for the ratio of the fertilizers and obtaining a forecast by weight. For example, the data on the fertilizers were introduced – N– 8, P_2O_5– 12, K_2O – 50, N + S - 82, P_2O_5 + SS– 68, K_2O + SS– 32. The yield of the forecast model is 25 t/ha, which is in good agreement with the experimental data. In Figure 6 is shown the result of the processing this example.

Figure 7 shows the relationship between the experimental data (target axis) and the expected data (output axis) on the test and training sample. As it can be seen from the figure, the results predicted by ANN are not close to the experimental ones, which confirm the quality of the model. The blue dots in Figure 7 show the results of the study of the miscanthus productivity, for the introduction of the sewage sludge at a rate of 20-40 t/ha and compost based on them in the range (22.4–27.1 t/ha). Basically, the forecast data fall on the

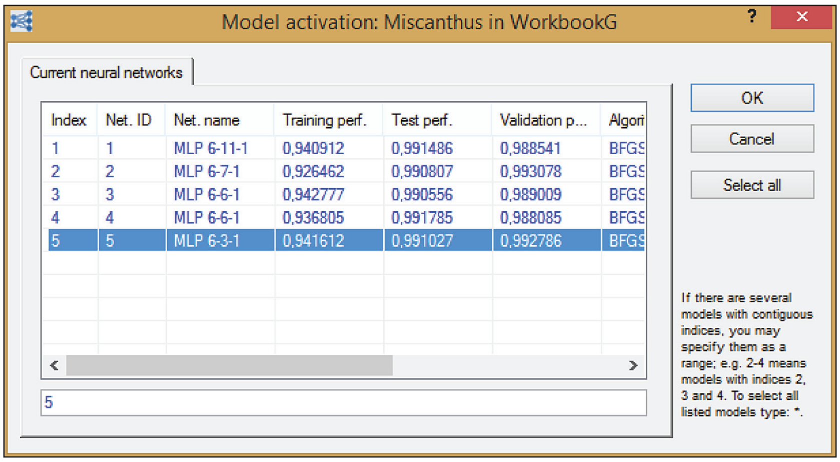

Figure 5. The result of the artificial neural networks

Table 4. The results of the sensitivity assessment

Networks	Sensitivity analysis (Miscanthus)					
	P_2O_5+SS	K_2O+SS	P_2O_5	K_2O	N	Nss
MLP 6-3-1	102.5177	26.48016	15.12288	2.642002	1.797092	1.357134

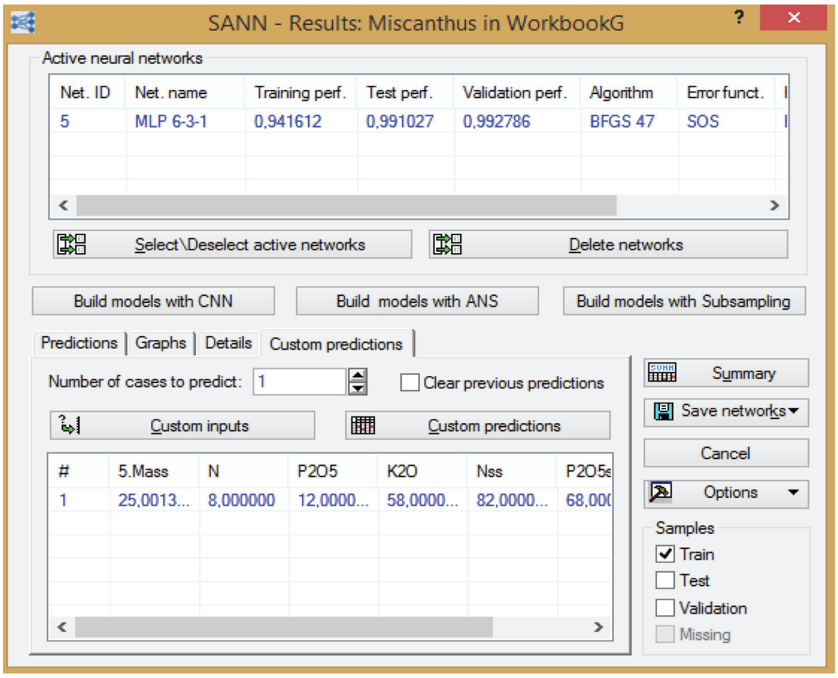

Figure 6. Forecasting the yield of the vegetative mass of the miscanthus (t/ha) according to the set values of the fertilizer application based on the sewage sludge

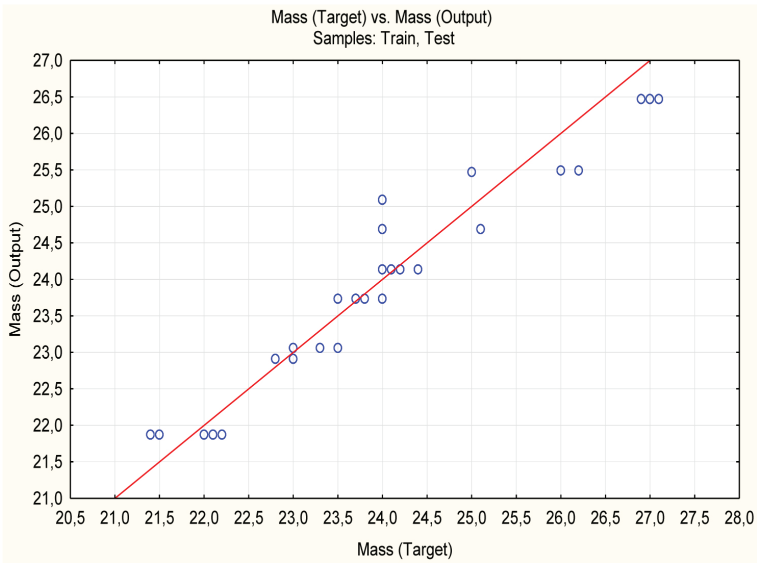

Figure 7. The relationship between the experimental and predicted data on the vegetative mass of the miscanthus

red line (the red line is the complete coincidence of the forecast and the experiment) with a small deviation, i.e. 0.3%.

CONCLUSIONS.

The artificial neural networks are widely used in various fields of knowledge, namely to predict the productivity of the agrophytocenoses of the energy crops. This research technology – artificial neural networks – is a mathematical model that allows finding the relationships between variables and predicted results of the studied variables, depending on the initial conditions. According to the obtained results, it can be successfully used to predict the productivity of the different energy crops in line with the given input parameters (fertilizer rates, basic agrochemical indicators, crop productivity). In this study, a mathematical model which allowed predicting the yield of the miscanthus at given levels, with the introduction of the mineral and organic (sewage sludge) fertilizers, was successfully implemented. According to the performed studies, the application of a sewage sludge in norm of 20–40 t/ha promotes productivity of the power cultures (the miscanthus) within 24.5–27.1 t/ha; thus, it increases productivity on 2.3–5.1 t/ha, compared with control.

REFERENCES

1. AEBIOM 2017. Statistical Report. European Bioenergy Outluk. Calderon C., Gauthier G., Jossart J.-M. et al. (Eds.) Brussels: European Biomass Association (AEBIOM), p. 264. Access: http://www.aebiom.org/ statistical-report-2017/statistical-report-2017-17-10
2. Alexopoulou E., Eleftheriadis I. 2010-2012 Role of 4F cropping in determining future biomass potentials, including sustainability and policy related issues. Biomass Department of CRES, p. 8. http://www.biomassfutures. eu/public_docs/final_deliverables/WP3/D3.2%20Role%20 of%204F%20crops.pdf
3. Cherubini F. and Strømman A.H. 2011. Life cycle assessment of bioenergy systems: state of the art and future challenges. Bioresource Technology, 102(2), 437-451.
4. Commission Staff Working Document 2014. State of play on the sustainability of solid and gaseous biomass used for electricity, heating and cooling in the EU. Brussels, SWD (2014) 259 final.
5. Dagli, C.H. (Ed.). 2012. Artificial neural networks for intelligent manufacturing. Springer Science & Business Media.
6. Directive 2009 EC of the European Parliament and of the Council of 23.04.2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/ EC
7. Dondini M., Hastings A., Saiz G. et al. 2009 The potential of Miscanthus to sequester carbon in soils: comparing field measurements in Carlow, Ireland to model predictions. Global Change Biology Bioenergy, 1–6, 413–425.
8. Fantozzi F. and Buratti C. 2010. Life cycle assessment of biomass chains: Wood pellet from short rotation coppice data measured on a real plant. Biomass and Bioenergy, 34, 1796-1804.
9. Felten D., Fröba N., Fries J., Emmerling C. 2012. Energy Balances and Greenhouse Gas Mitigation Potentials of Bioenergy Cropping Systems (Miscanthus, Rapeseed, and Maize) based on Farming Conditions in Western Germany. Renewable Energy, 55, 160–174. https://doi.org/10.1016/j.renene.2012.12.004
10. Grytsulyak G. and Lopushniak V. 2016. Impact of sewage sludge application on the humus state of sod-podzolic soil of subcarpathia under energetic willow plantation. Agricultural Science and Practice, 2, 26–32. https://doi.org/10.15407/agrisp
11. Heller, M., Keoleian, G., Volk, T. 2003. Life cycle assessment of a willow bioenergy cropping system. Biomass Bioenergy, 25, 147–65.
12. Heaton E. and Giant 2010. Miscanthus for biomass production. Biomass: miscanthus. AG201, 1-2.
13. Karlik B. and Olgac A.V. 2011. Performance analysis of various activation functions in generalized MLP architectures of neural networks. International Journal of Artificial Intelligence and Expert Systems, 1(4), 111-122.
14. Lopushniak V. and Hrytsuliak H. 2020. Environmental soil conditions for entering sewage sludge under energy crops Proceedings of the XXII International Scientific and Practical Conference/ International Trends in Science and Technology. Vol. 1. Warsaw, Poland. 57-60.
15. Lopushniak V.I., Yakubovskyi T., Shpik N.R., Hrytsuliak H.M., 2018. The ecological model of the reclamation of the degraded sod-podzolic soils of the Precarpathian region. Scientists of Lviv National Agrarian University in production: a catalog of the innovative developments. 18 edition. Lviv: Lviv National Agrarian University, 7-8.
16. Miscanthus agronomy (for fuel and industrial uses): final project report NF0403. Ministry of agriculture, fisheries and food. Great Britain, 1999. Access: www.ienica.net/usefulreports/miscanannex.pdf
17. Miscanthus, its place in uk agriculture and farming: UK Agriculture. United Kingdom. Access: www.ukagriculture.com/crops/miscanthus.cfm.
18. Nussbaumer T. 2004. Evaluation of Biomass Combustion based Energy Systems by Cumulative Energy Demand and Energy Yield Coefficient. – Zurich: Verenum press. 47 p. Report to International Energy Agency IEA Bioenergy Task 32 and Swiss Federal Office of Energy. Access: http: // task32.ieabioenergy.com/wp-content/uploads/2017/03/Nussbaumer_IEA_CED_V11.pdf .
19. Nussbaumer T. and Oser M. 2004. Evaluation of biomass combustion based energy systems by cumulative energy demand and energy yield coefficient. Report for International Energy Agency and Swiss Federal Office of Energy, http://www.iea- bcc.nl/publications/Nussbaumer_IEA_CED_ V11.pdf
20. Proposal for a Directive of the European Parliament and the Council on the promotion of the use of energy from renewable sources (recast). Brussels, 23.2.2017, COM (2016) 767 final/2. Mode of access: http://eur-lex.europa.eu/legal- content/EN/TXT/?uri=CELEX:52016PC0767R(01)
21. Rojas R. 2013. Neural networks: a systematic introduction. Springer Science & Business Media. Report from the Commission to the Council and the European Parliament on sustainability requirements

for the use of solid and gaseous biomass sources in electricity, heating and cooling. Brussels, 25.2.2010. COM(2010. http://eur-lex.europa.eu/legal- content/EN/TXT/?qid=1410874845626&uri=CELEX:520 1 0DC0011

22. Roik M.V., Kurilo V. L, Ganzhenko O.M, Gumenyk M.Ya. 2012. Prospects for the development of bioenergy in Ukraine. Sugar Beets, 2-3, 6–8
23. Rokitova O. 2010. The energy biofuel crops: the miscanthus - pros and cons. International Bioenergy, 2010. http://www.infobio.ru/analytics/ 385.html.
24. Saleha Almardeai, Juan-Rodrigo Bastidas-Oyanedel, Sabeera Haris, Jens Ejbye Schmidt, 2017. Avicennia marina biomass characterization towards bioproducts Emirates Journal of Food and Agriculture, 29(9), 710-715.
25. Haykin S. 2009. Neural networks and learning machines. Pearson Education. Upper Saddle River, NJ. 33–35.
26. Specht, D.F. 1990. Probabilistic neural networks. Neural Networks, 3(1), 109–118.
27. Ramlia S., Radub S., Shaaric K., Rukayadib Y. 2020. Toxicity analysis of Syzygium polyanthum (Wight) Walp. leaves extract and its stability against different pH and temperature Emirates Journal of Food and Agriculture, 32(6), 461-468
28. Tryboi O.V. 2018. Efficient biomass value chains for heat production from energy crops in Ukraine. Energetika, 64(2), 84–92.
29. Vambol S., Vambol V., Sobyna V., Koloskov V., Poberezhna L. 2018. Investigation of the energy efficiency of waste utilization technology, with considering the use of low-temperature separation of the resulting gas mixtures, 64(4), 186–195.
30. Wagner M., Kiesel A., Hastings A., Iqbal Ya., Lewandovski I. 2017. Novel Miscanthus ger-mplasm-based value chains: a life cycle assess- ment. Frontiers in Plant Science, 8, Article 990, 1–18.
31. Xuejiao Ren, Jiabin Ci, Liangyu Jiang, Weiguang Yang, Wei Yang, 2018. Effects of physicochemical properties of different substrates on characters and yield of maize Emirates Journal of Food and Agriculture, 30(10), 851-862.
32. Leal Y.H., de Oliveira Sousa V.F., Dias T.J. 2020. Edaphic respiration in bell pepper cultivation under biological fertilizers, doses and application times. Emirates Journal of Food and Agriculture, 32(6), 434-442.
33. Zinchenko V. and Yashin M. 2011. The energy of the miscanthus. LesPromInform, 6(80). http://lesprominform.ru/jarchive/articles/itemshow/2409
34. Zheliezna T.A. and Drozdova O.I. 2014. Kompleksnyj analiz tehnologij proizvodstva jenergii iz tverdoj biomassy v Ukraine. Teploenergetika, 4, 16–20.